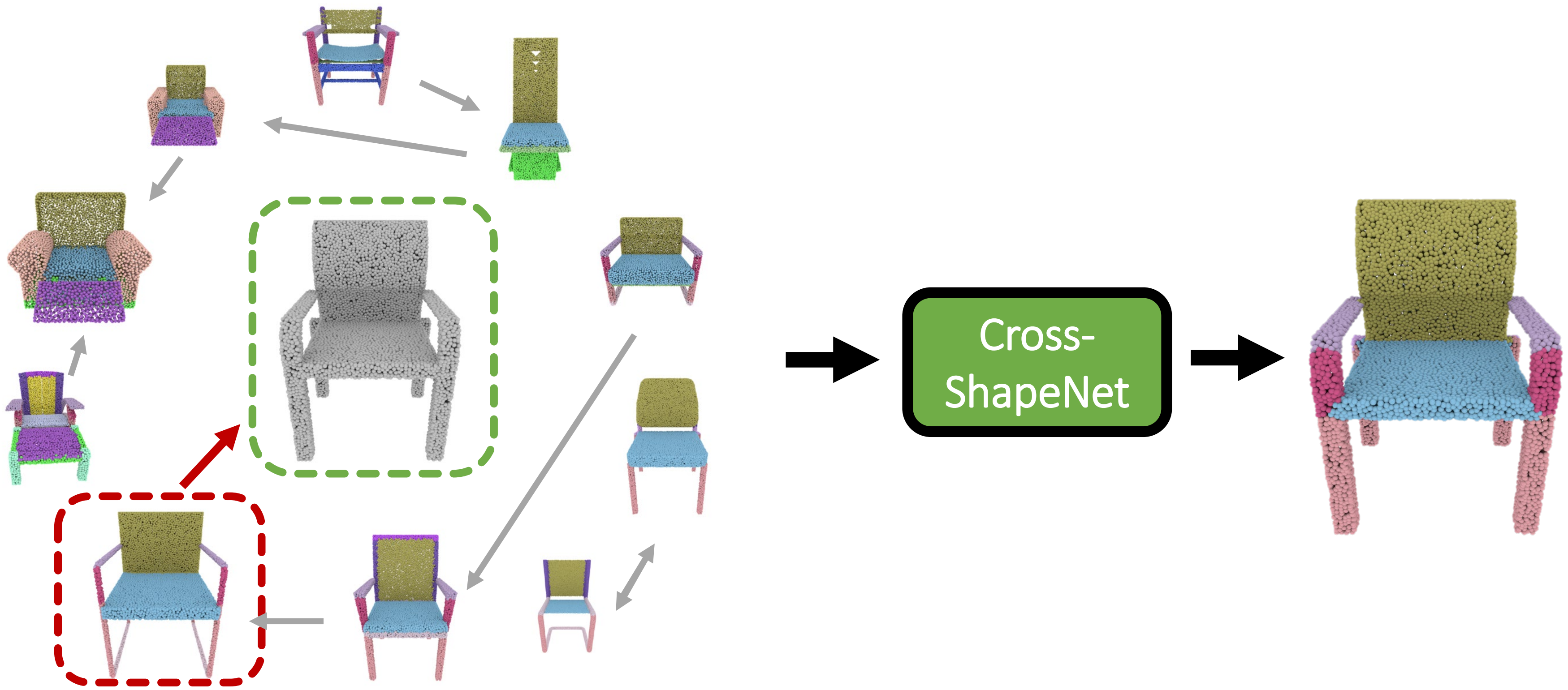
Cross-Shape Attention for Part Segmentation of 3D Point Clouds



Marios Loizou[†1] **Siddhant Garg [†2]** **Dmitry Petrov [†2]**

Melinos Averkiou[1] **Evangelos Kalogerakis[2]**

[1]University of Cyprus / CYENS CoE *[2]University of Massachusetts Amherst*

† Equal Contribution

Goal: learn more coordinated feature representations

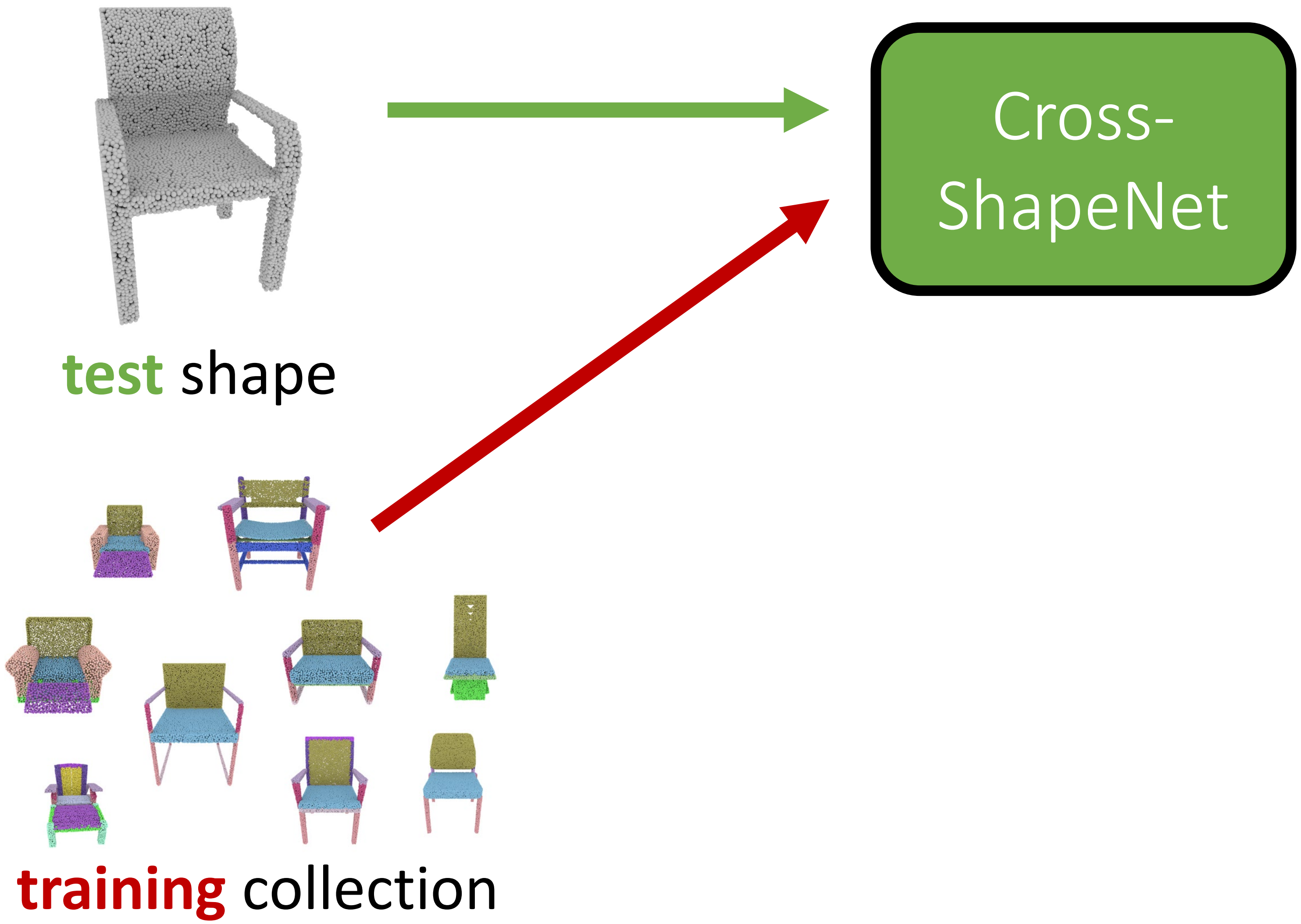
test shape

Goal: learn more coordinated feature representations

test shape

training collection

Goal: learn more coordinated feature representations



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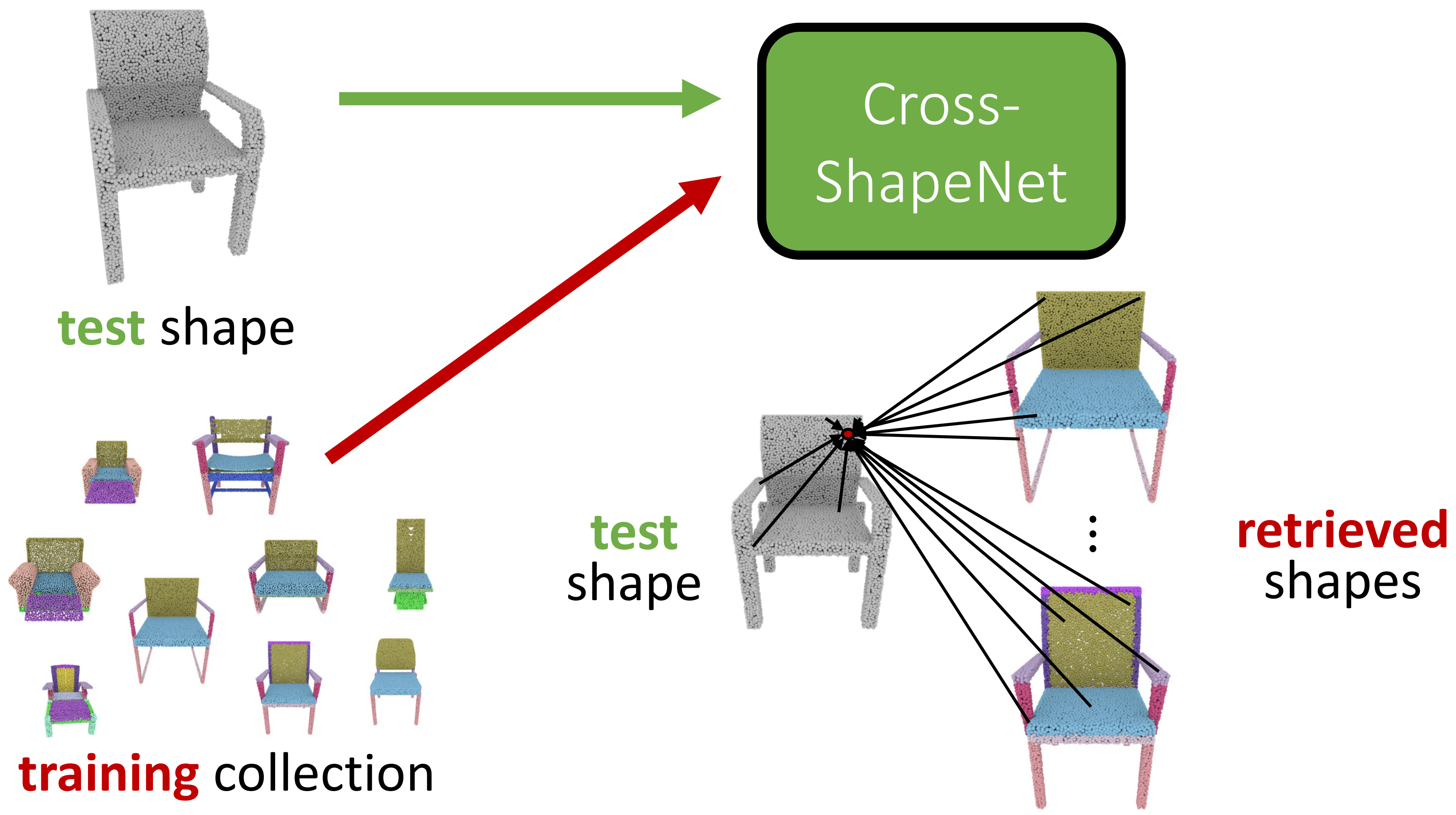

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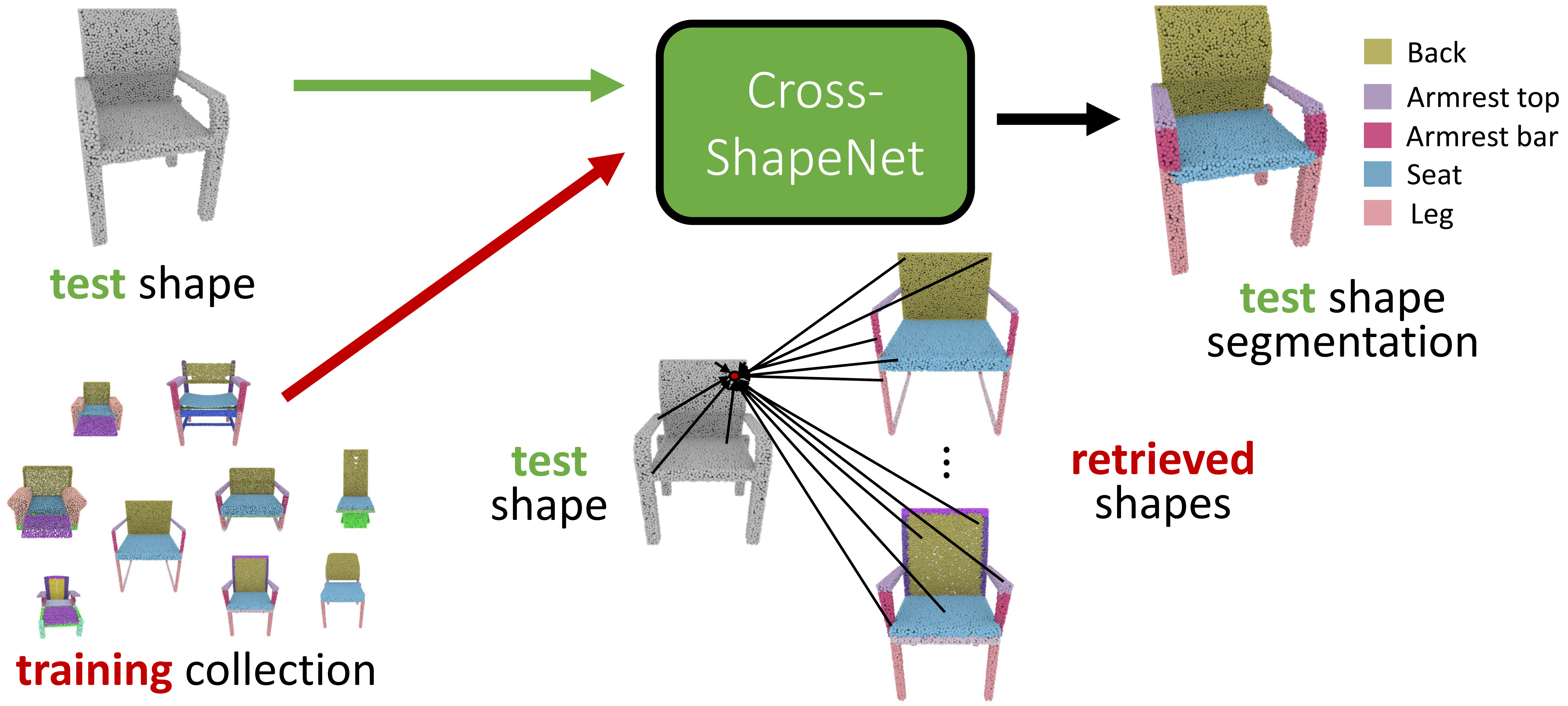
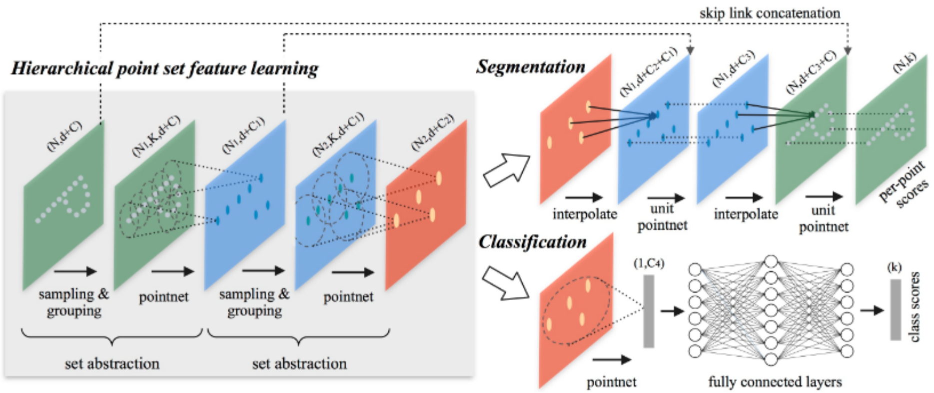


Prior work: Point-based networks



PointNet++ [Qi et al. 2017]

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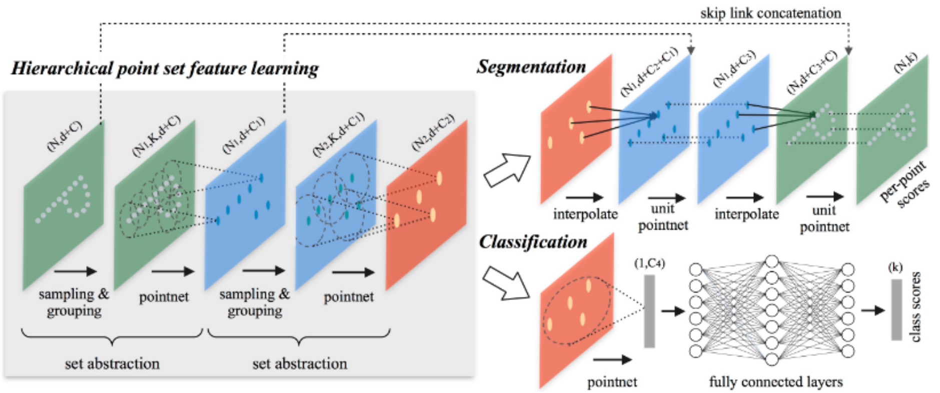

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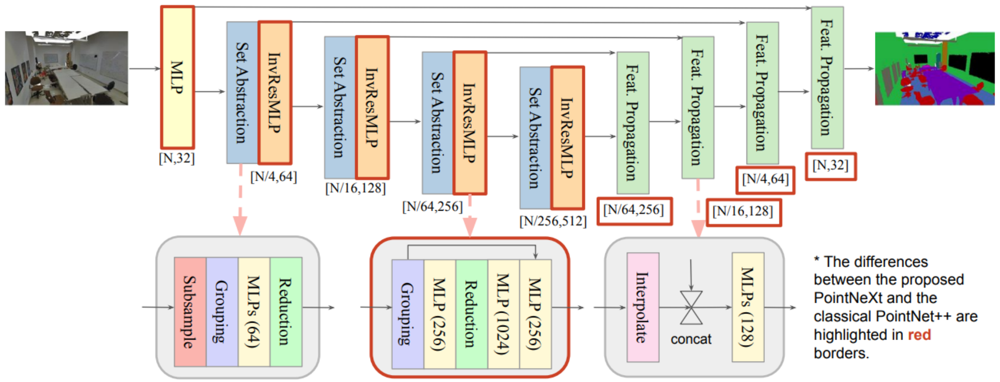
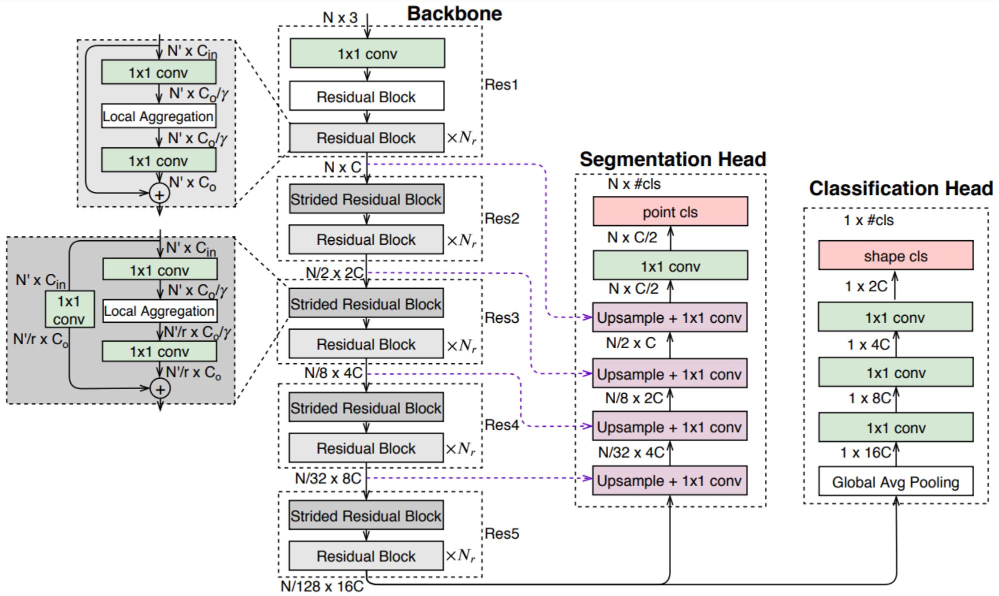
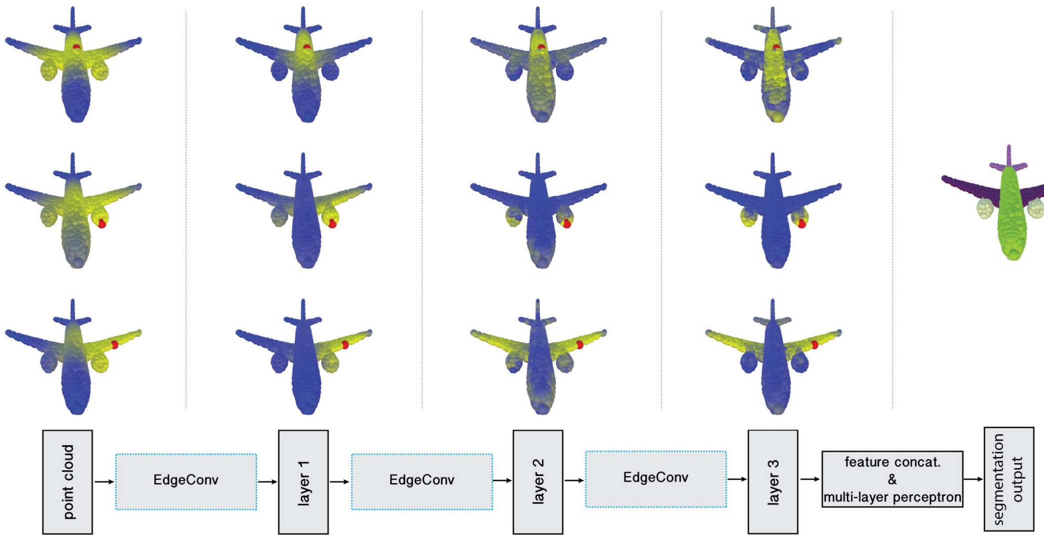


PointNeXt [Qian et al. 2022]

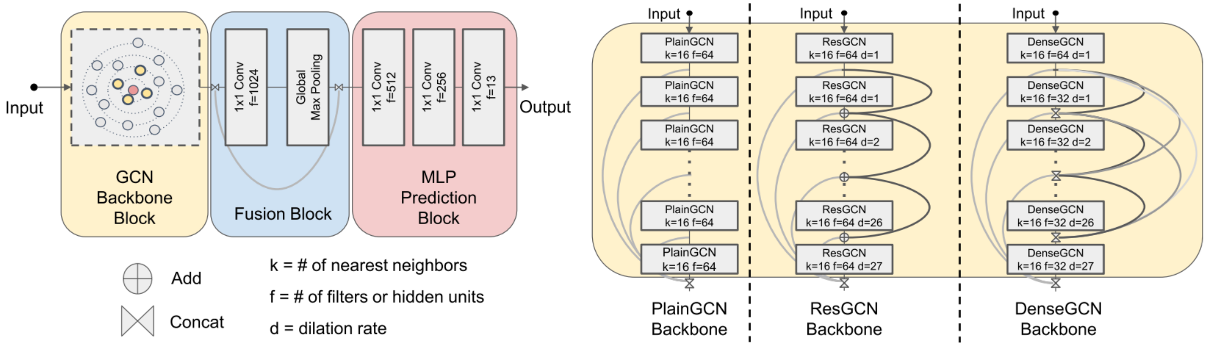


CloserLook3D [Liu et al. 2020]

Prior work: GCNs for non-Eucledian data

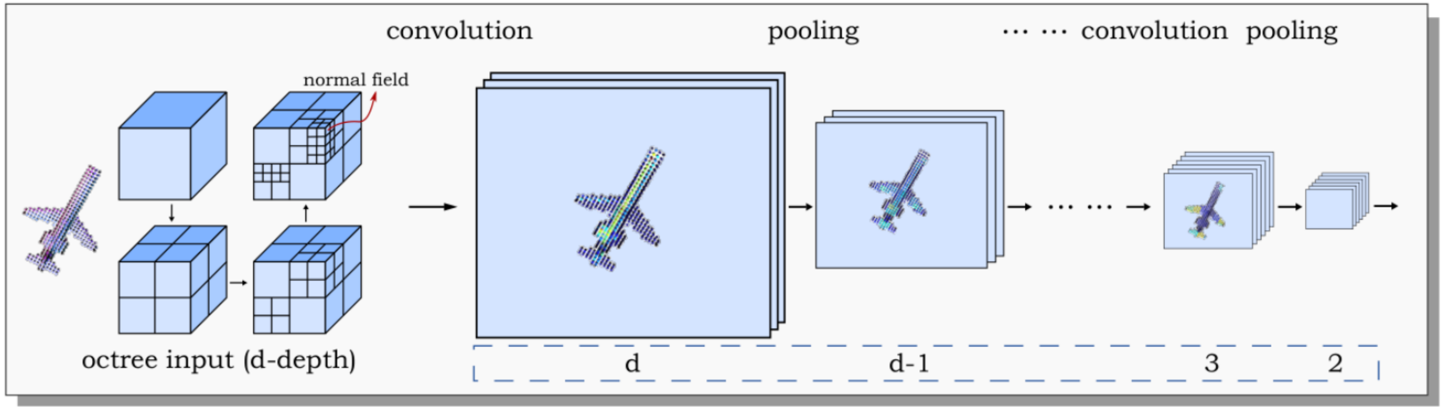


DGCNN [Wang et al. 2019]

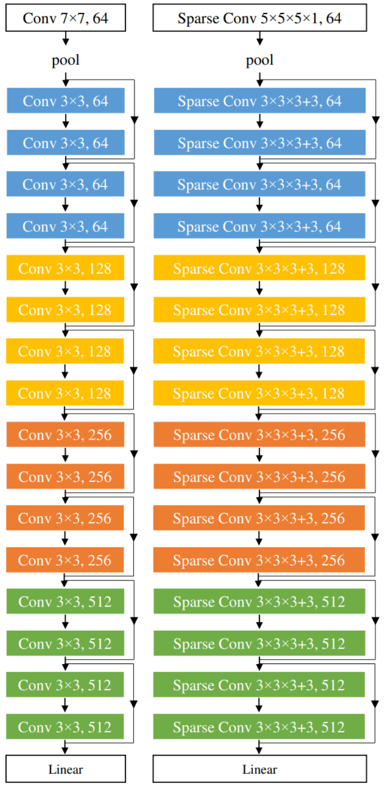


DeepGCNs [Li et al. 2023]

Prior work: Volumetric networks

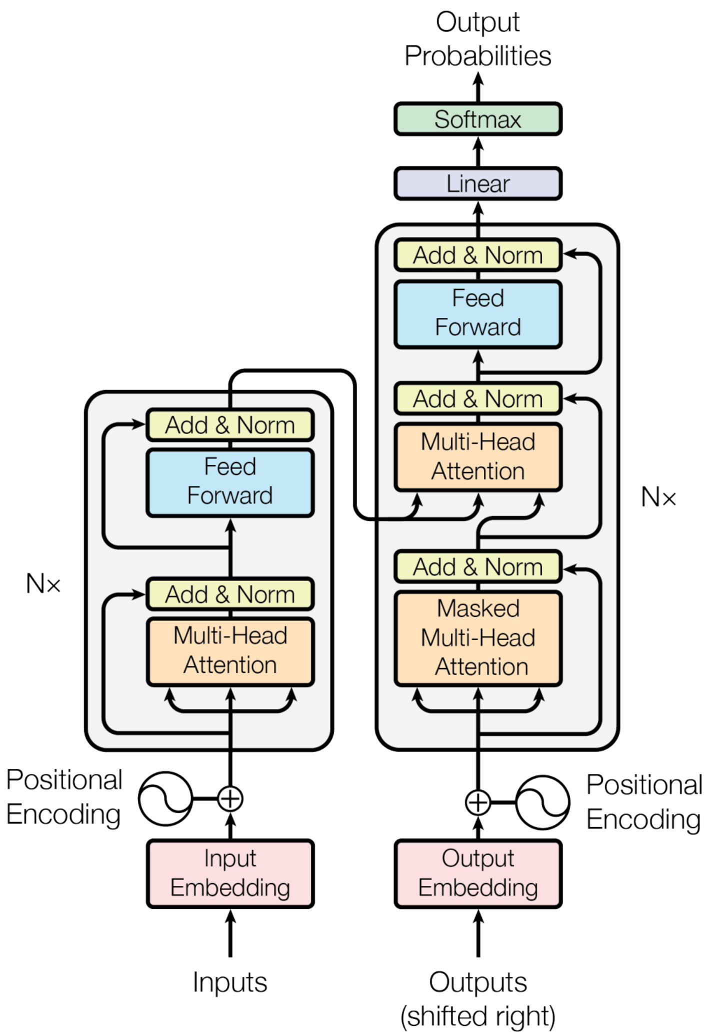


O-CNN [Wang et al. 2017]

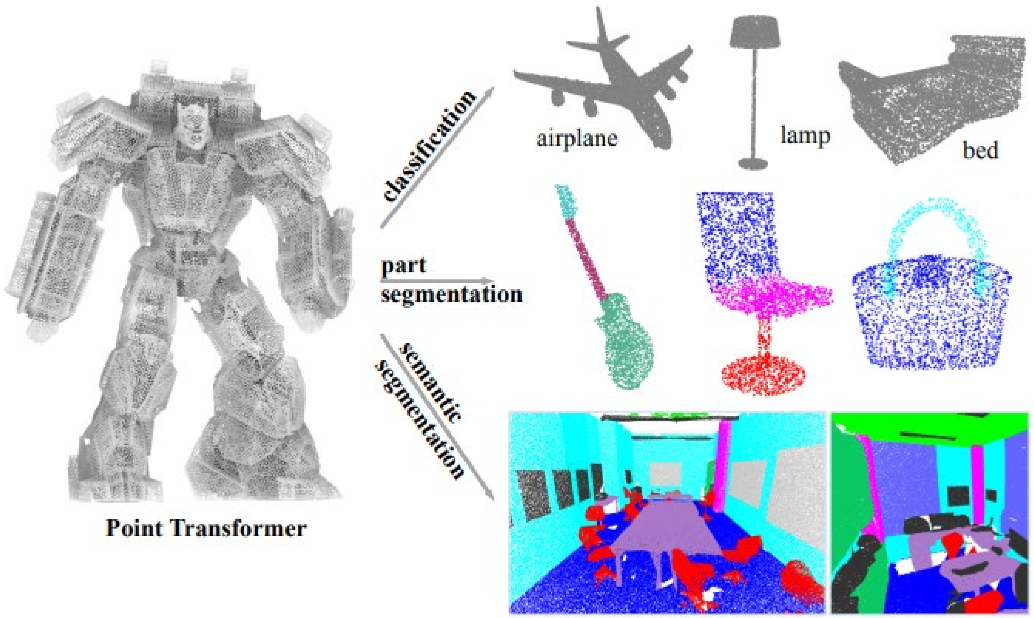


MinkowskiNet [Choy et al. 2019]

Prior work: Attention is All You Need



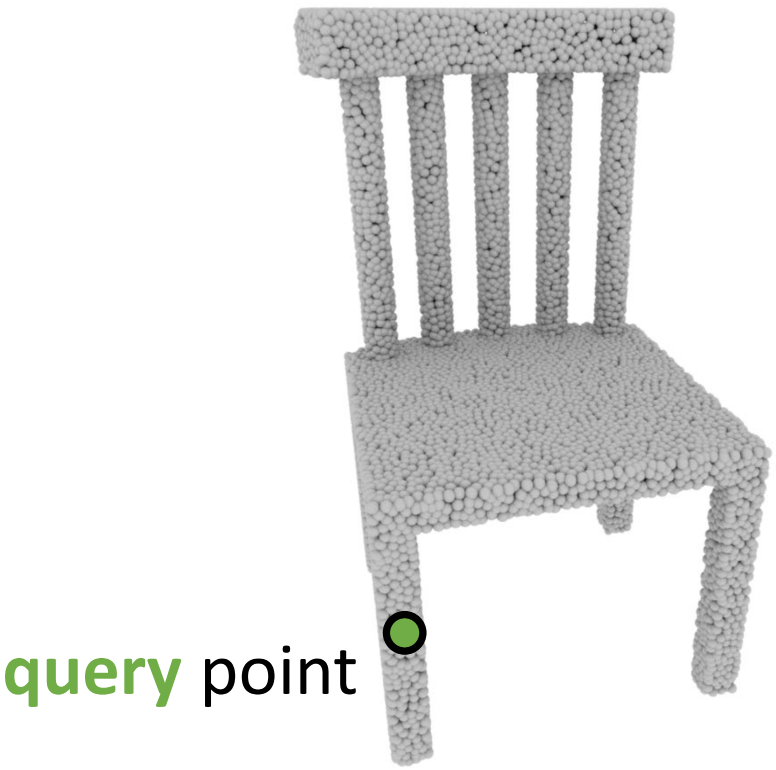
Transformer [Vaswani et al. 2017]



PointTransformer v1/v2 [Zhao et al. 2021, 2022]

Why use **attention** for 3D representations?

Encode points such that their features capture **relations** wrt the rest of the shape



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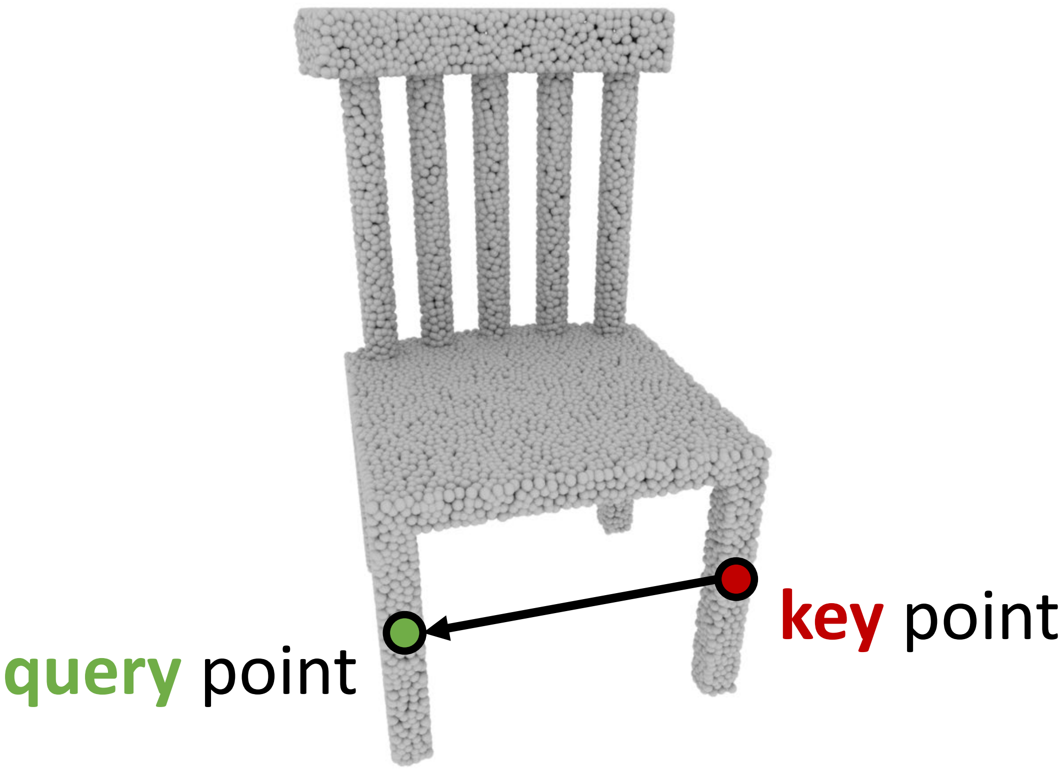

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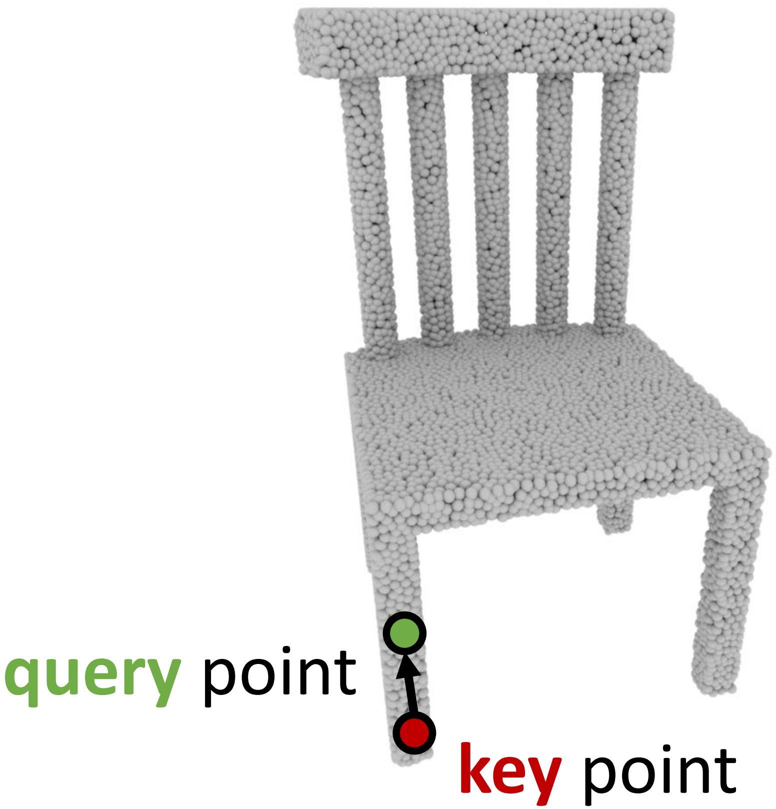

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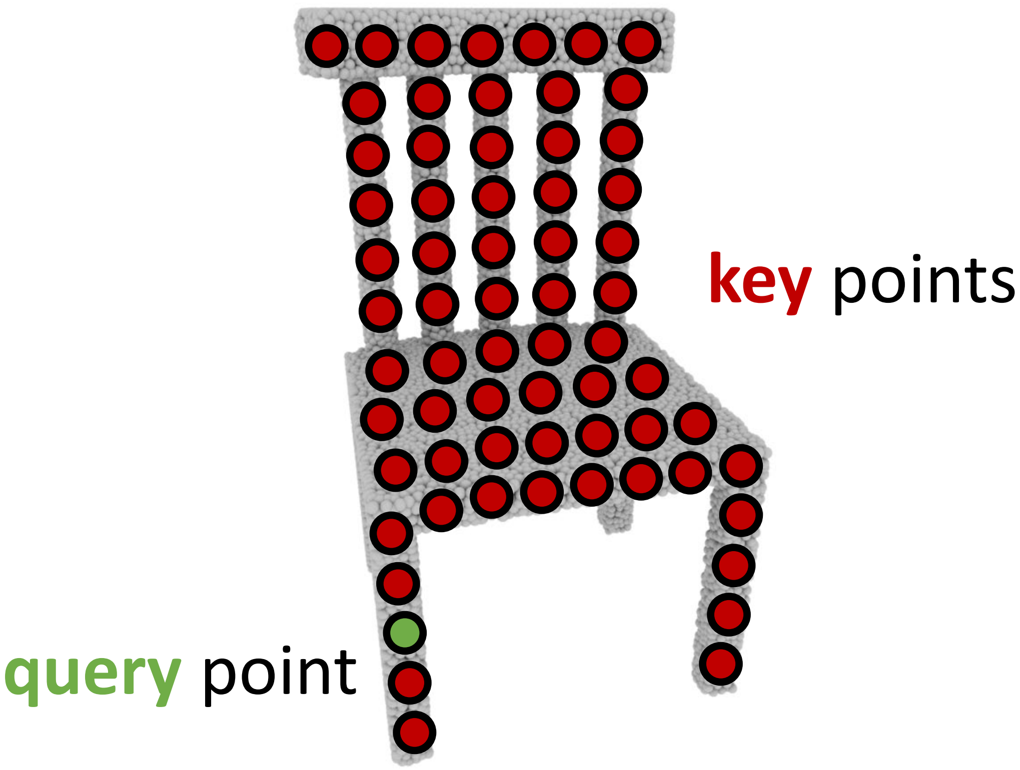

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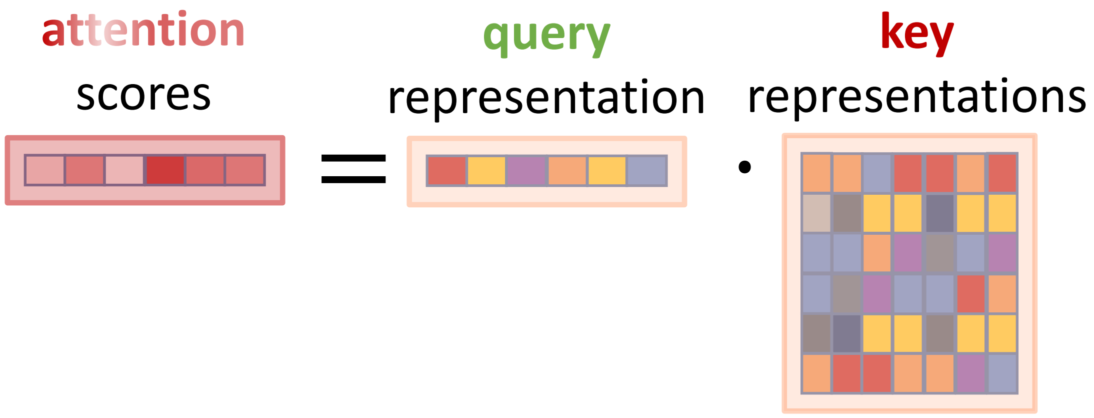

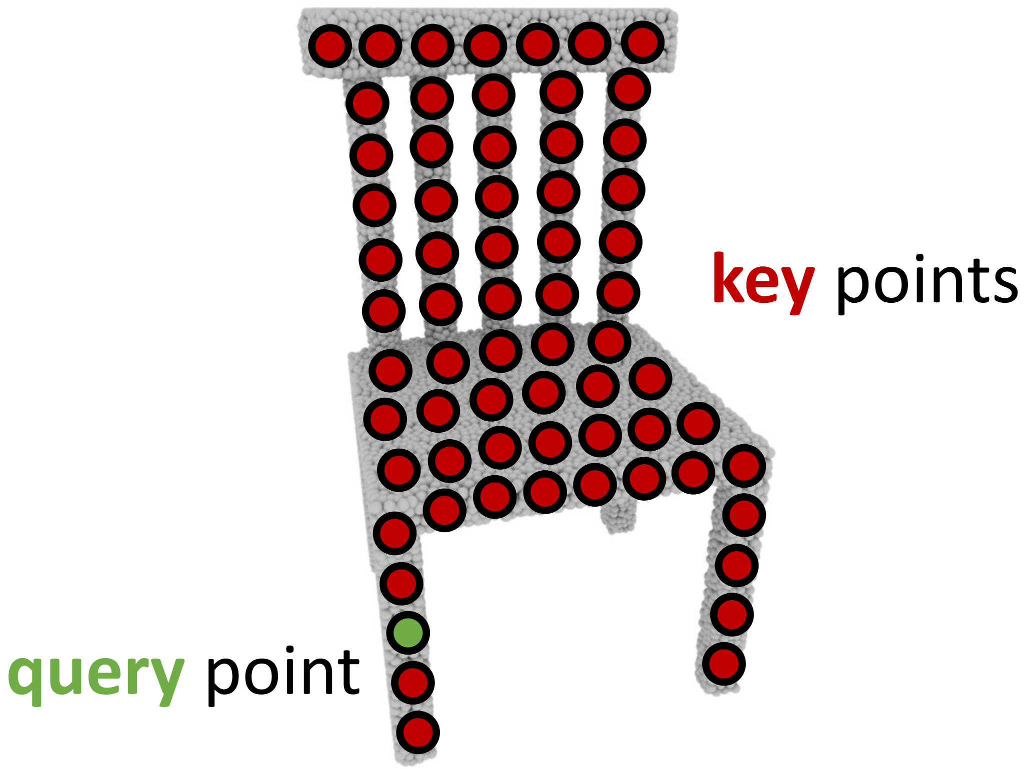

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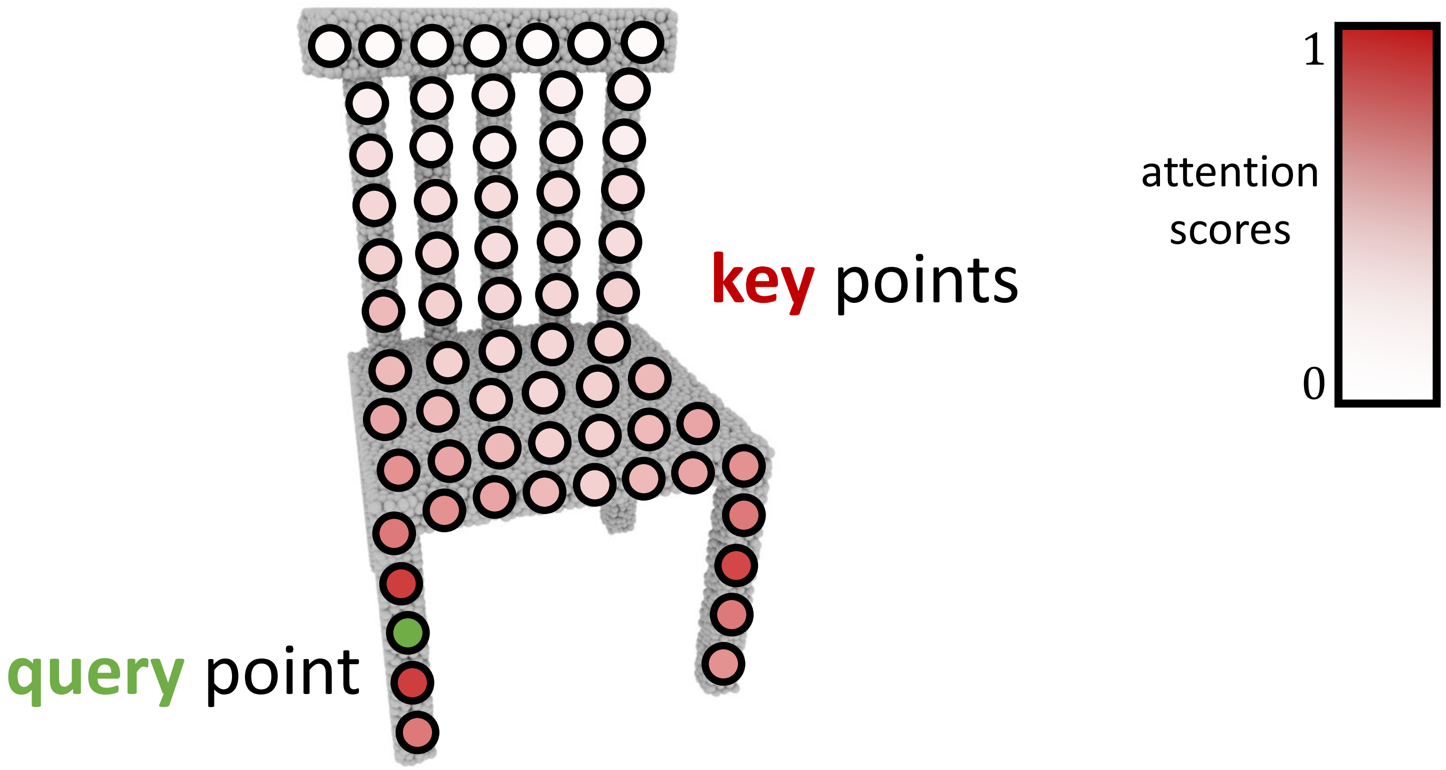

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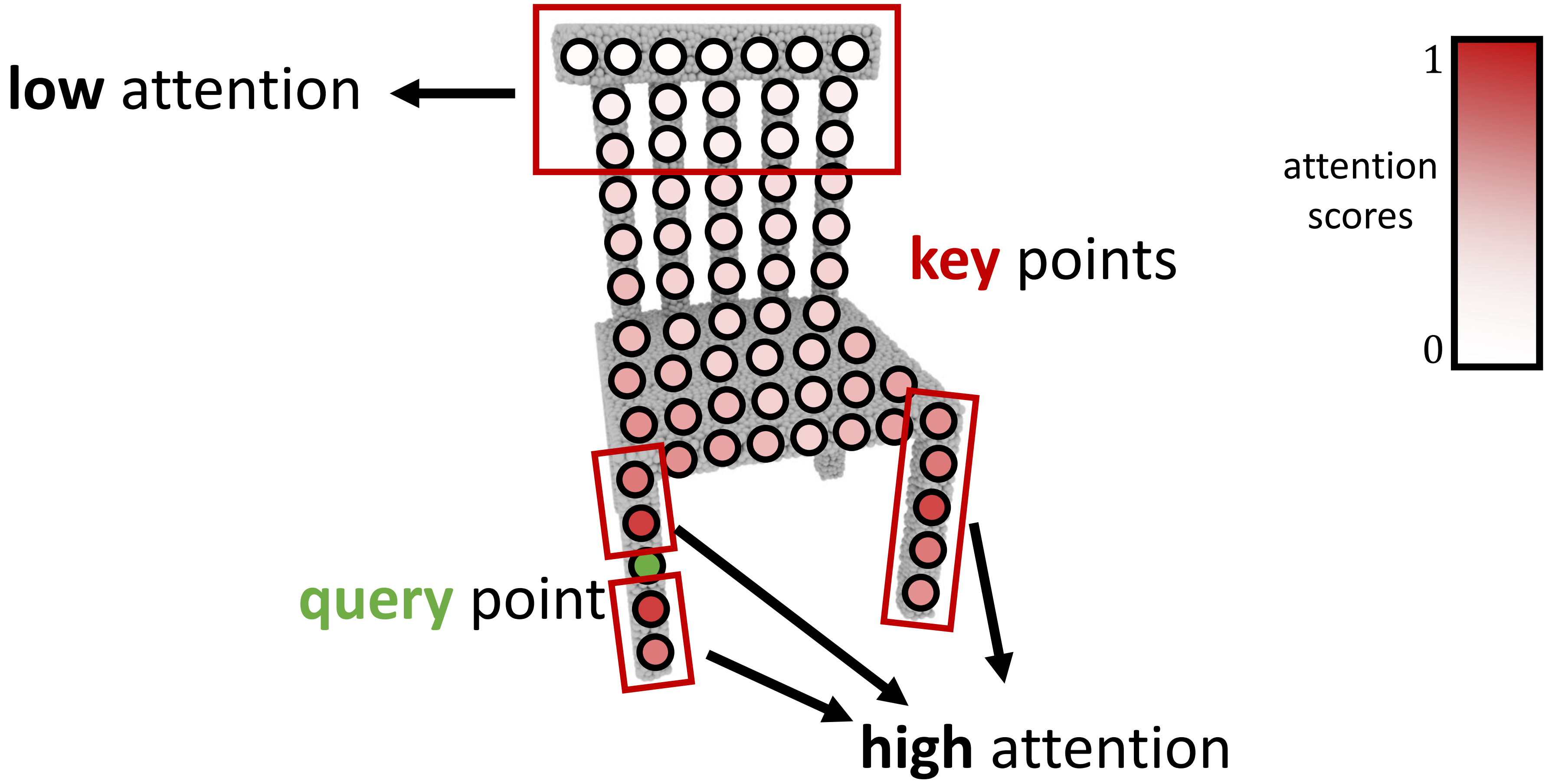

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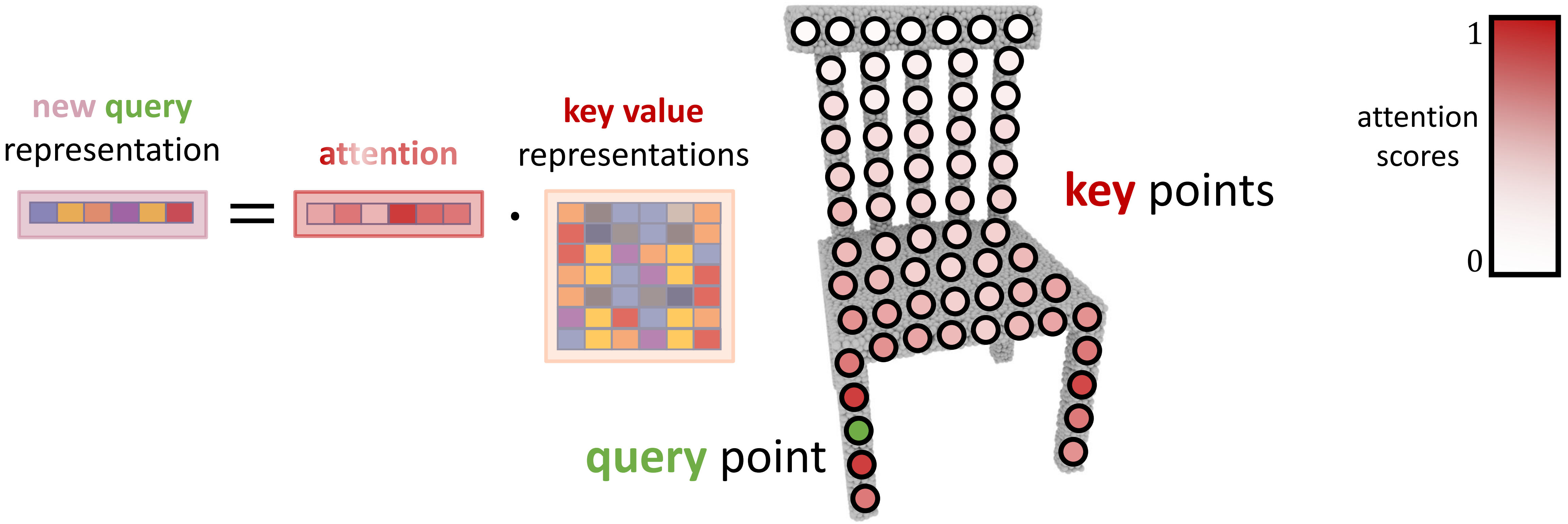

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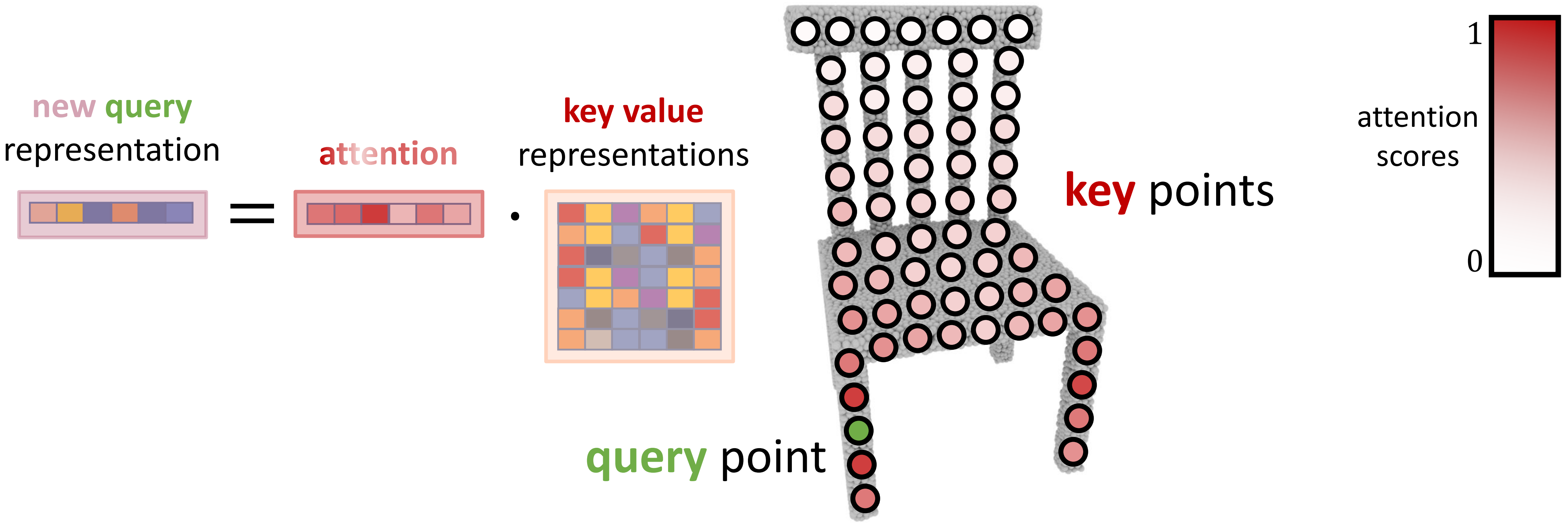

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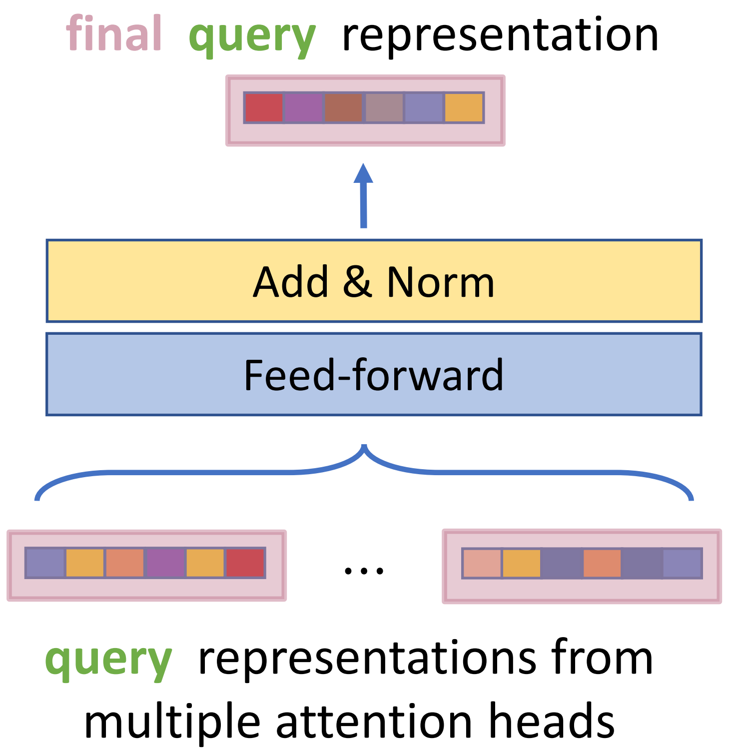
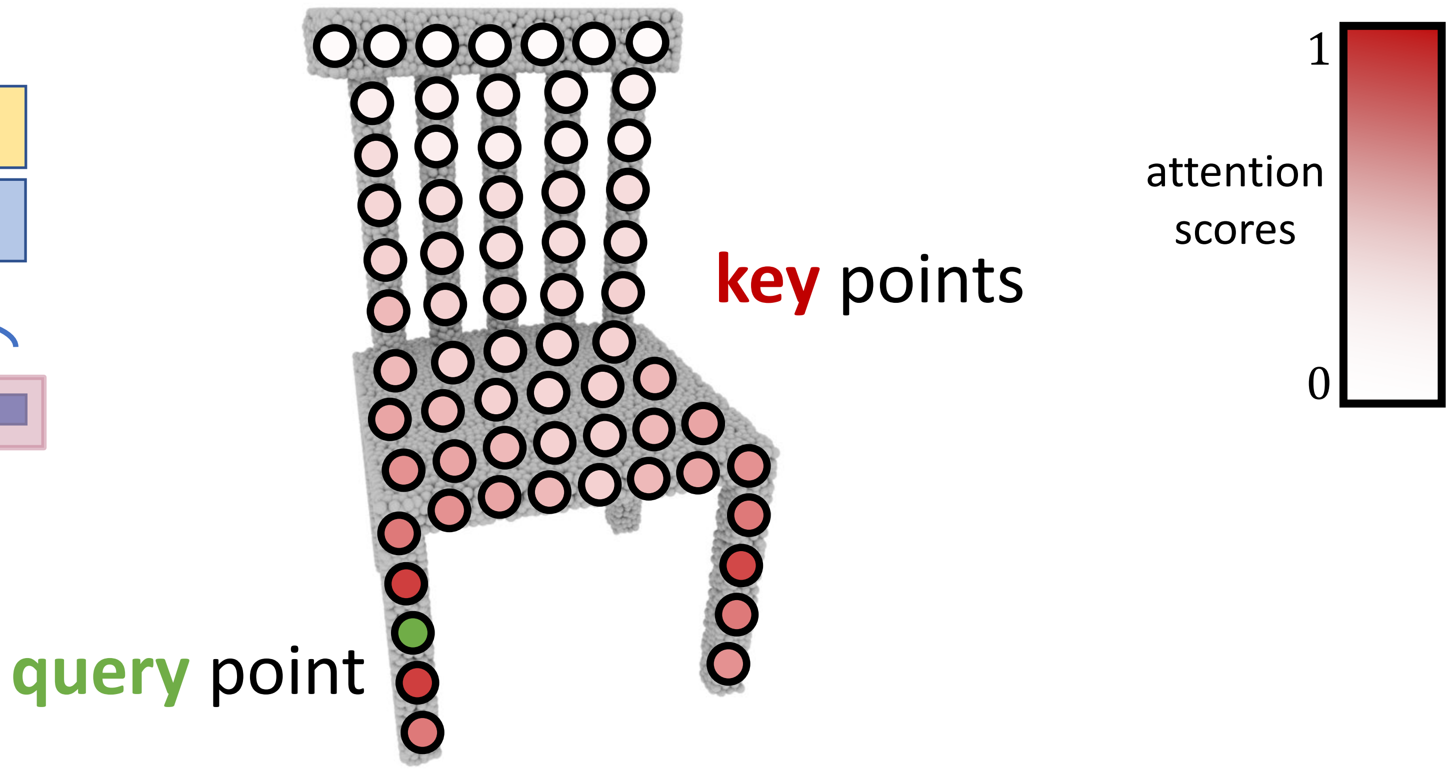




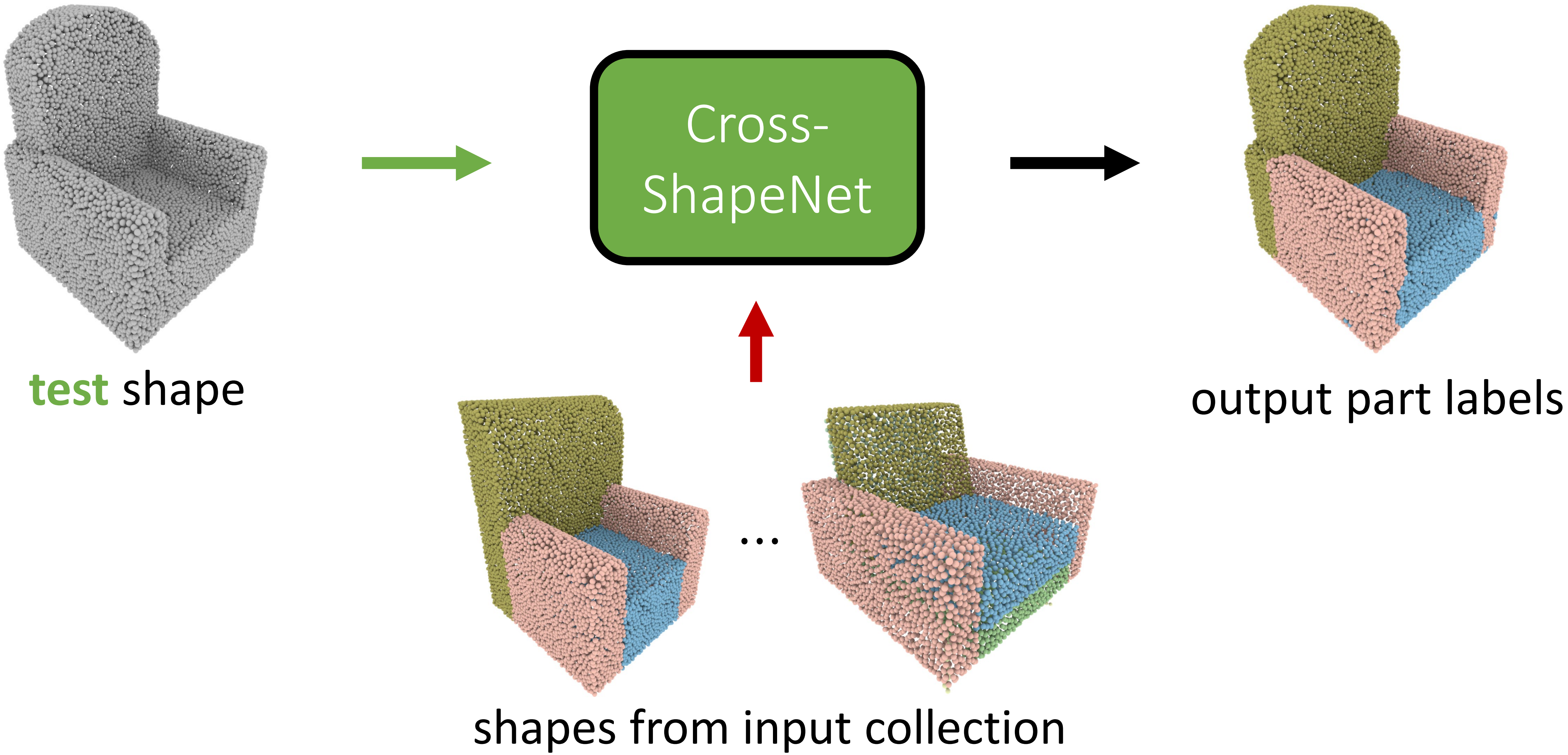
Motivation: Long-range interactions **across** shapes

test shape

output part labels

No interactions across shapes

Motivation: Long-range interactions across shapes

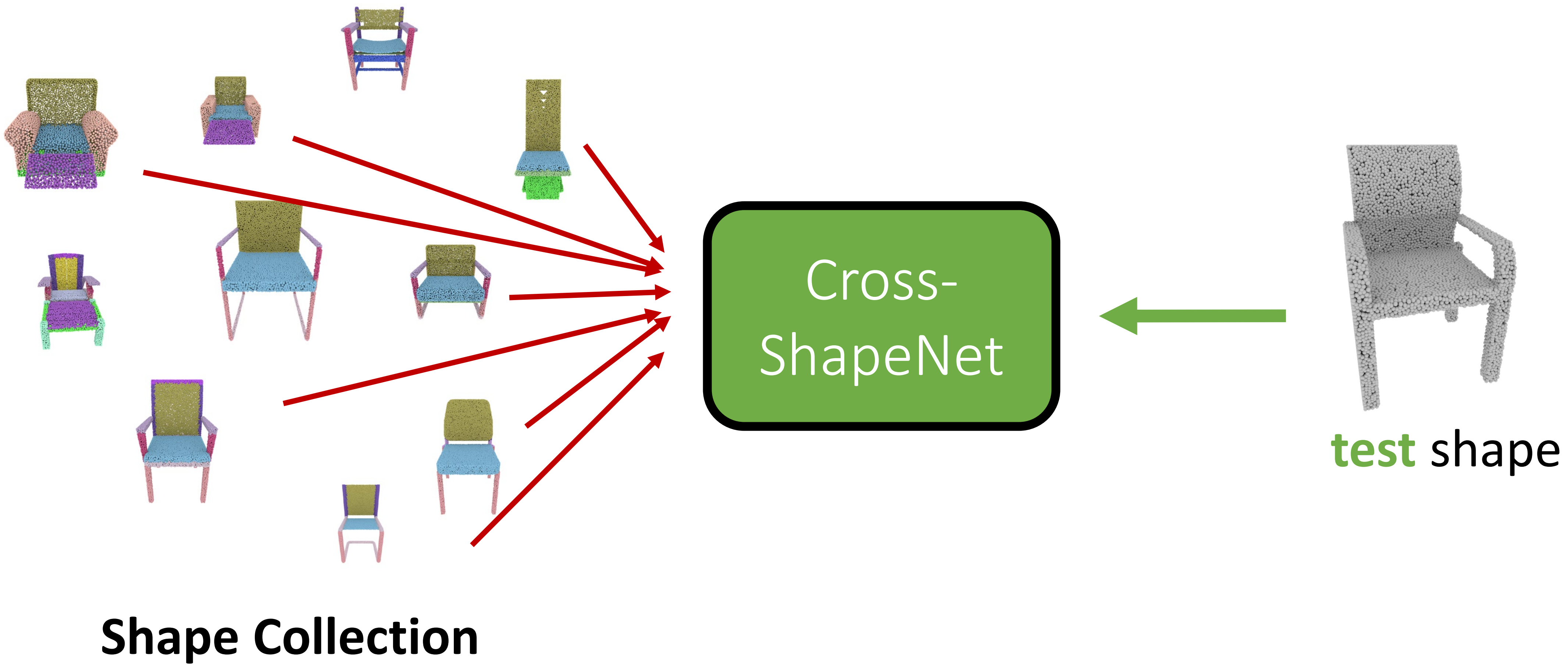


Key challenge: Retrieve compatible shapes

Shape Collection

test shape

Key challenge: Retrieve compatible shapes



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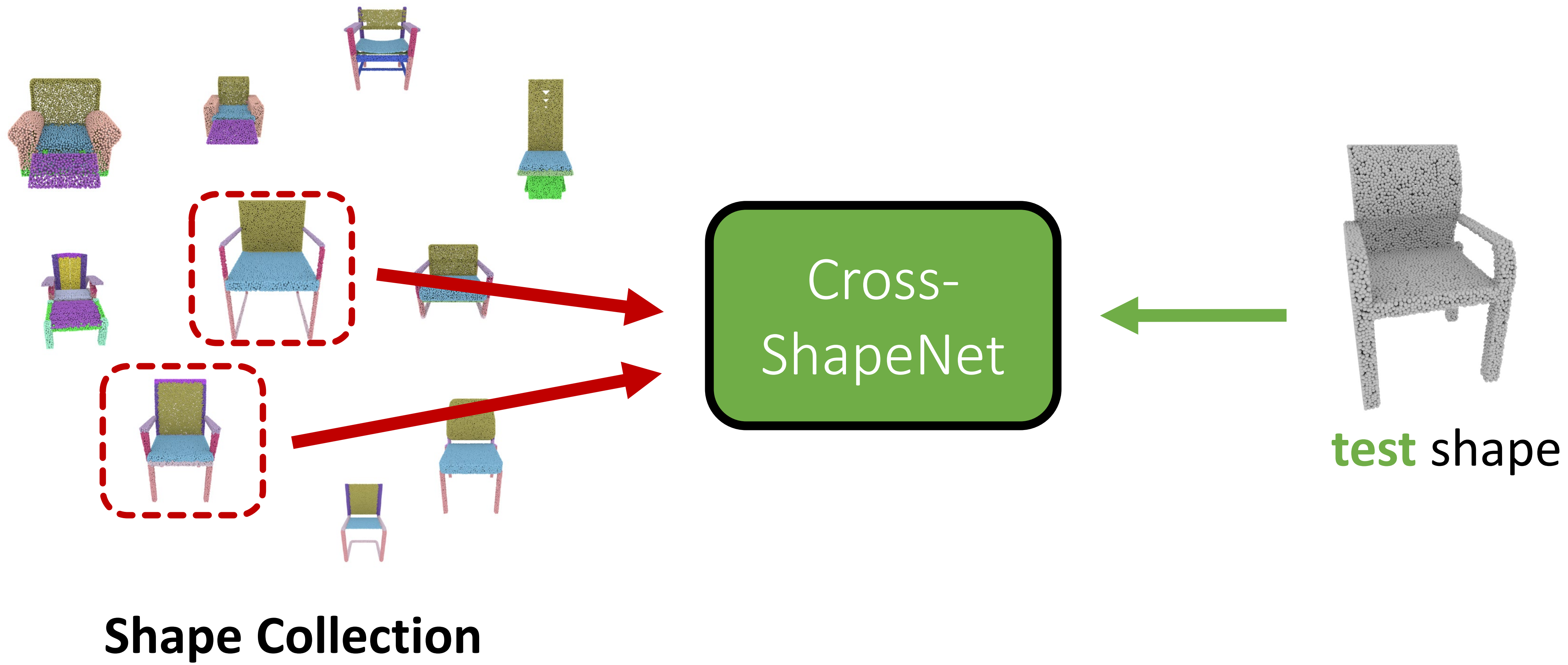
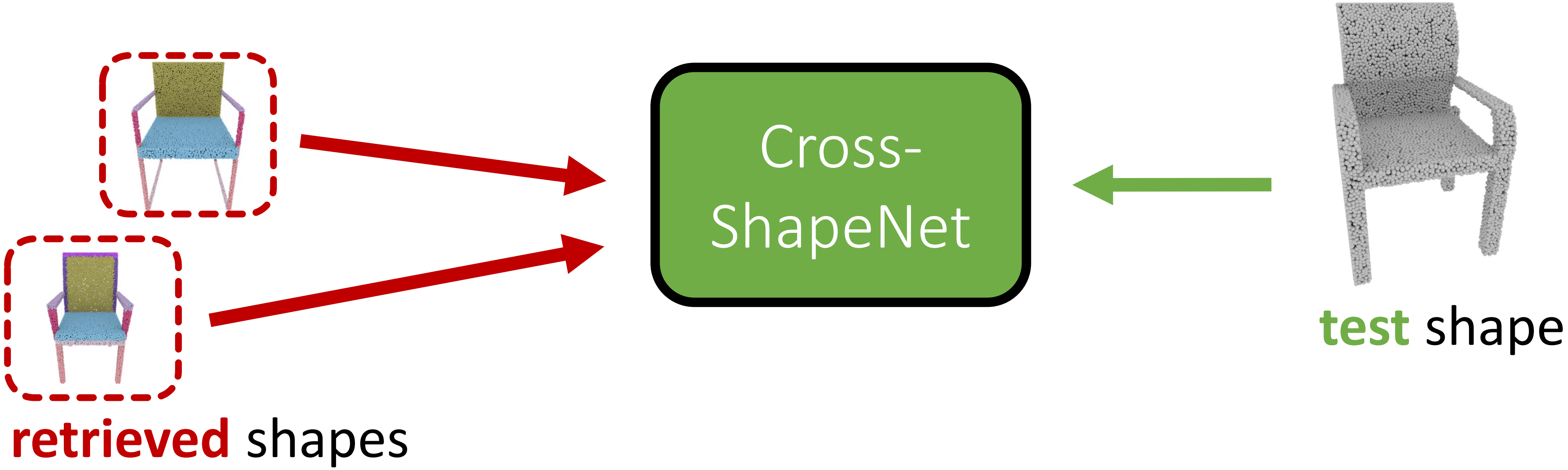


Key challenge: Combine multiple shapes



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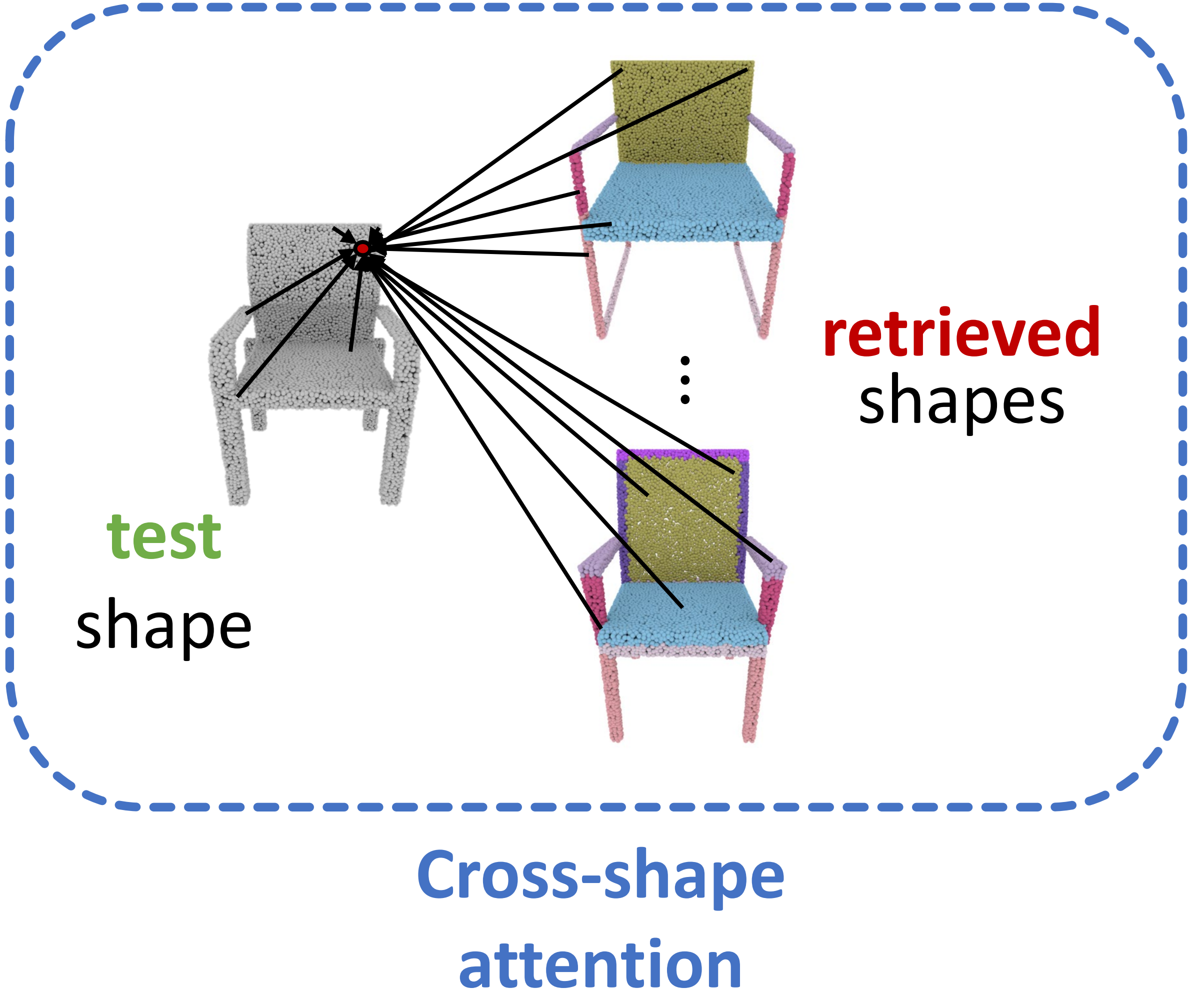

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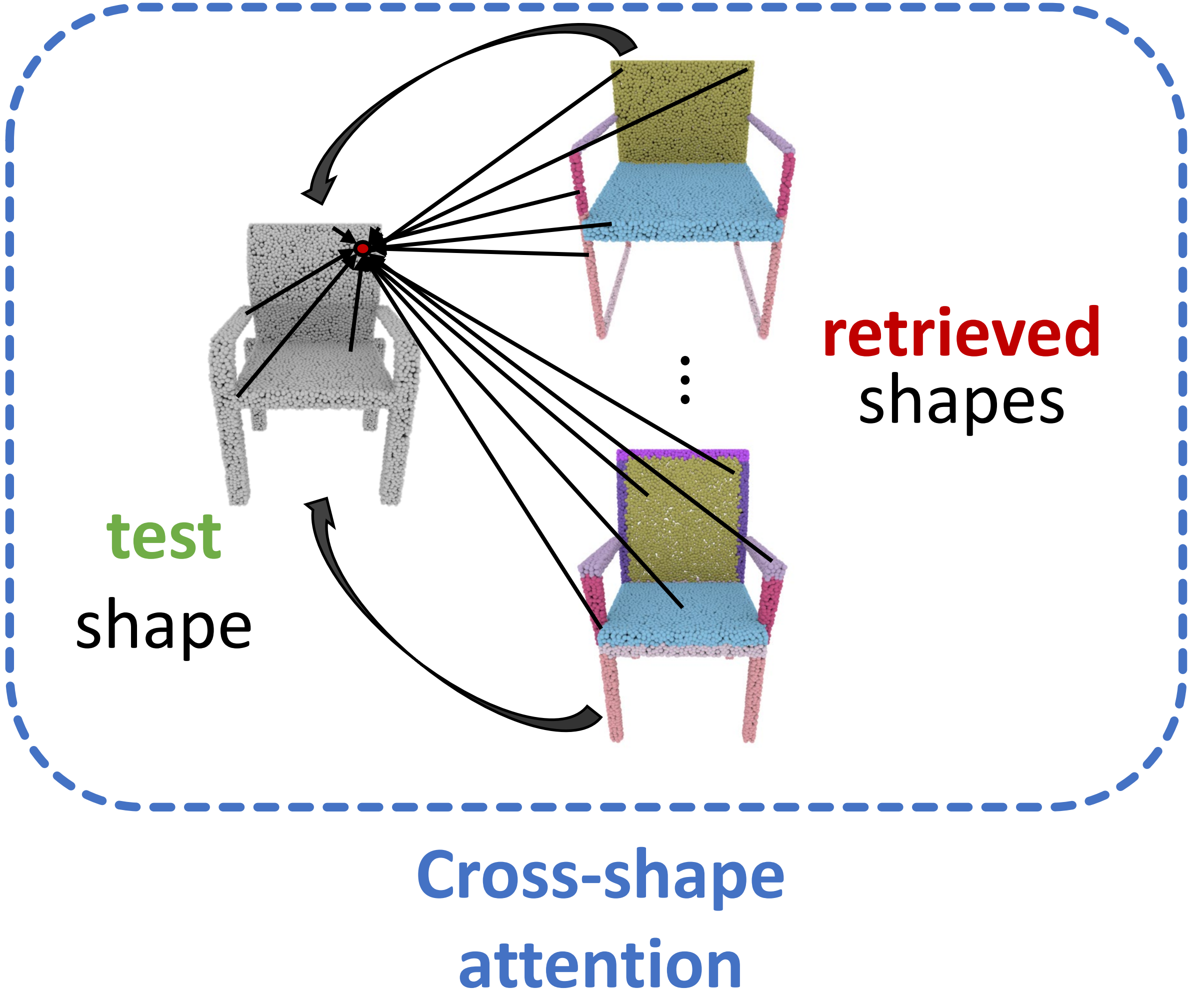
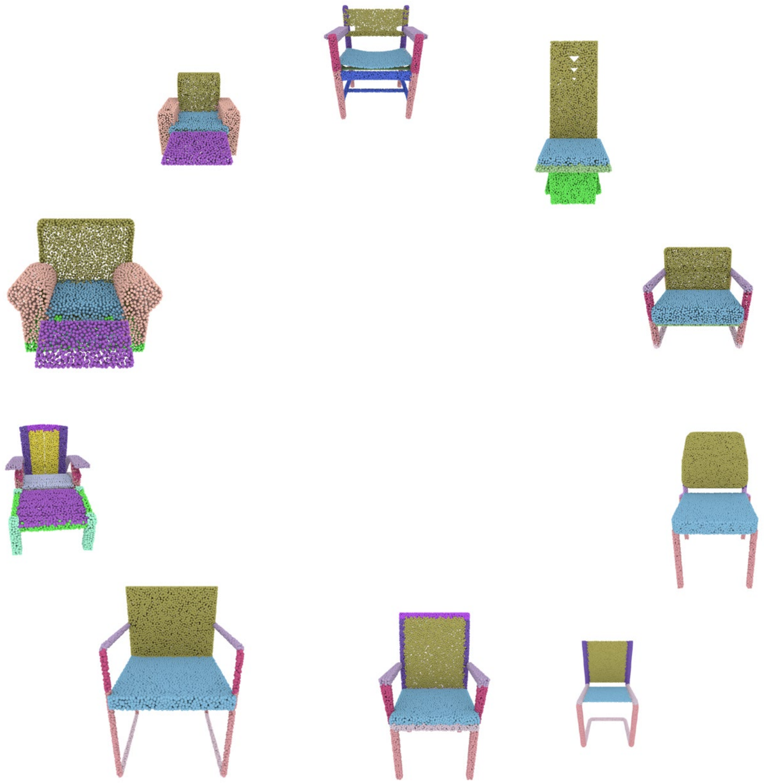
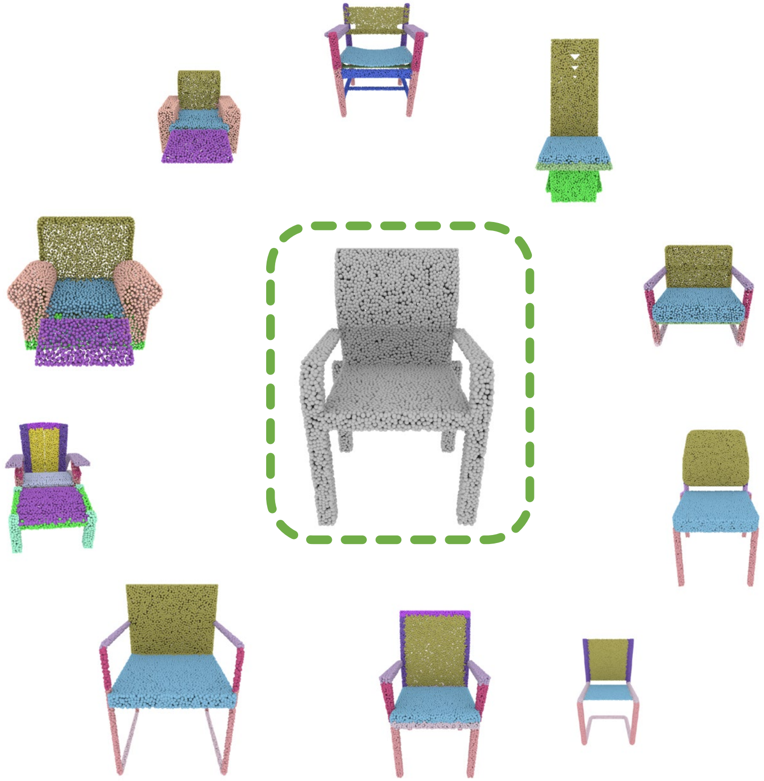


Pipeline



Shape Collection

Pipeline



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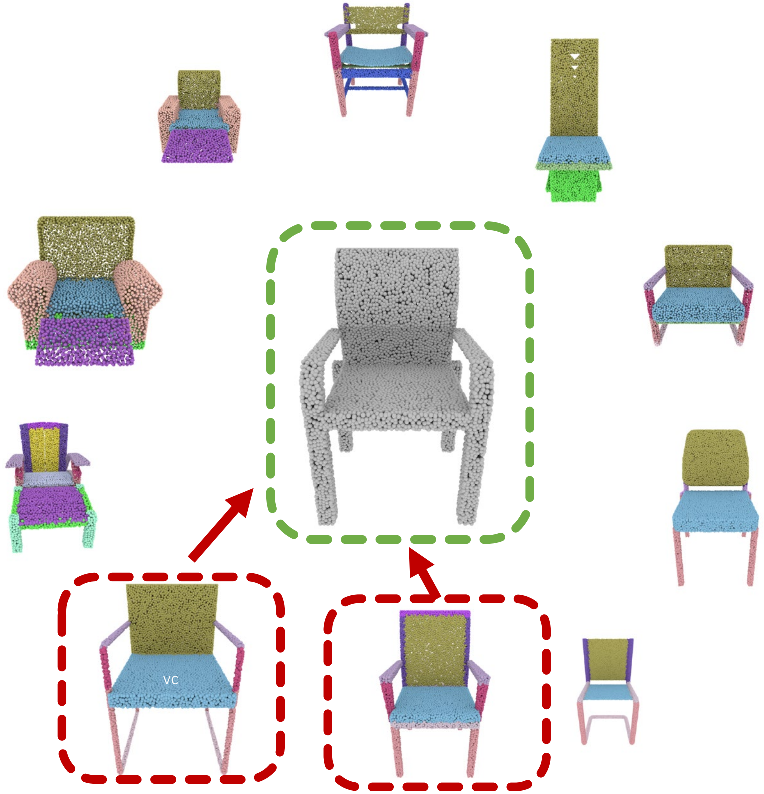

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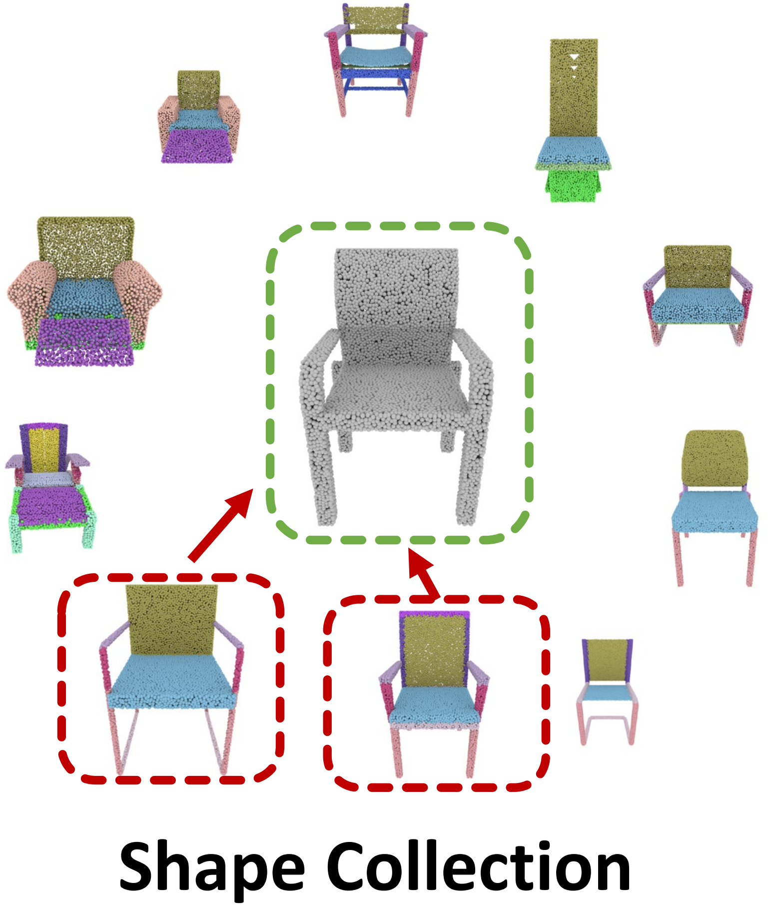

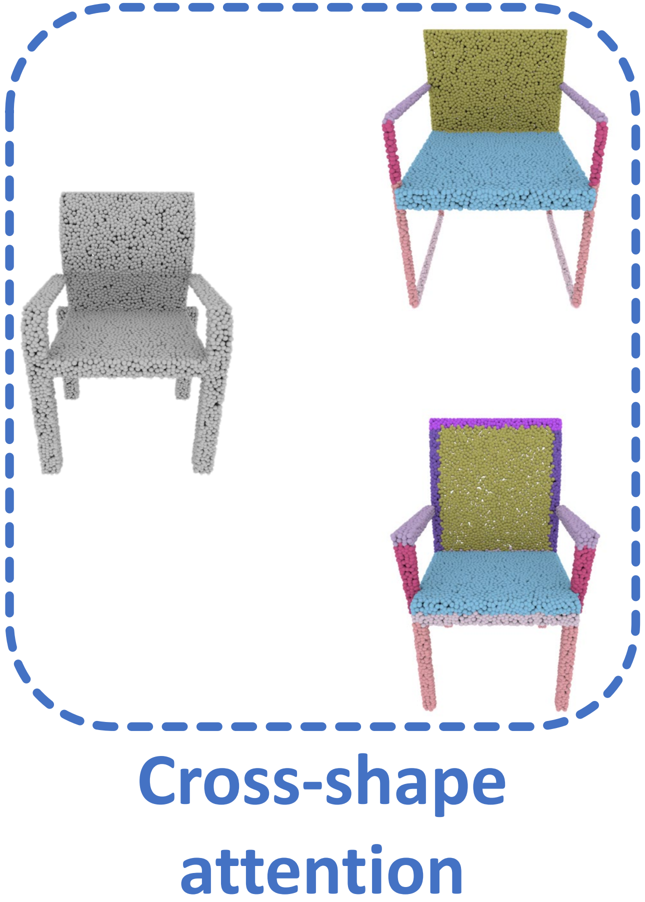

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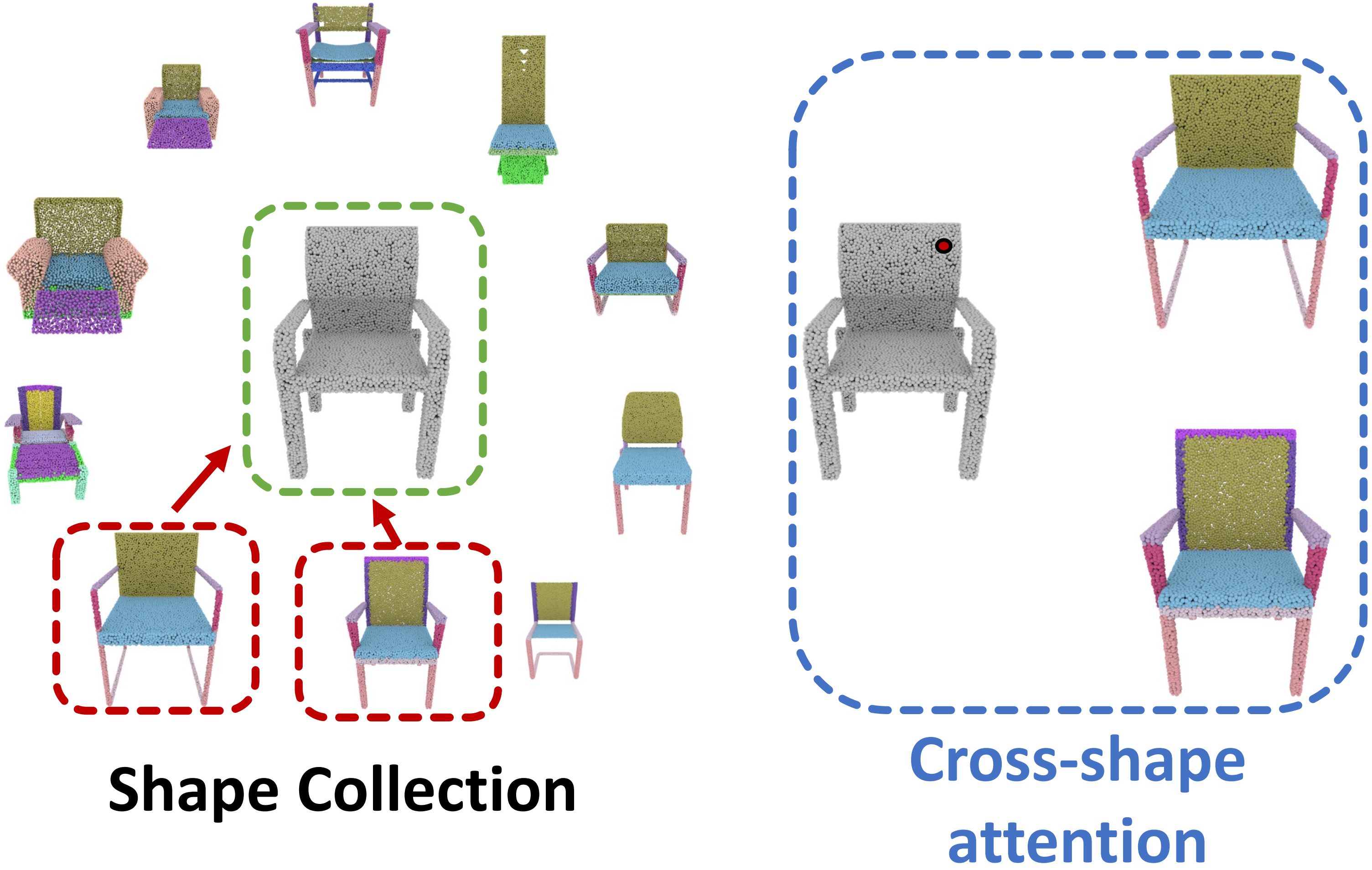

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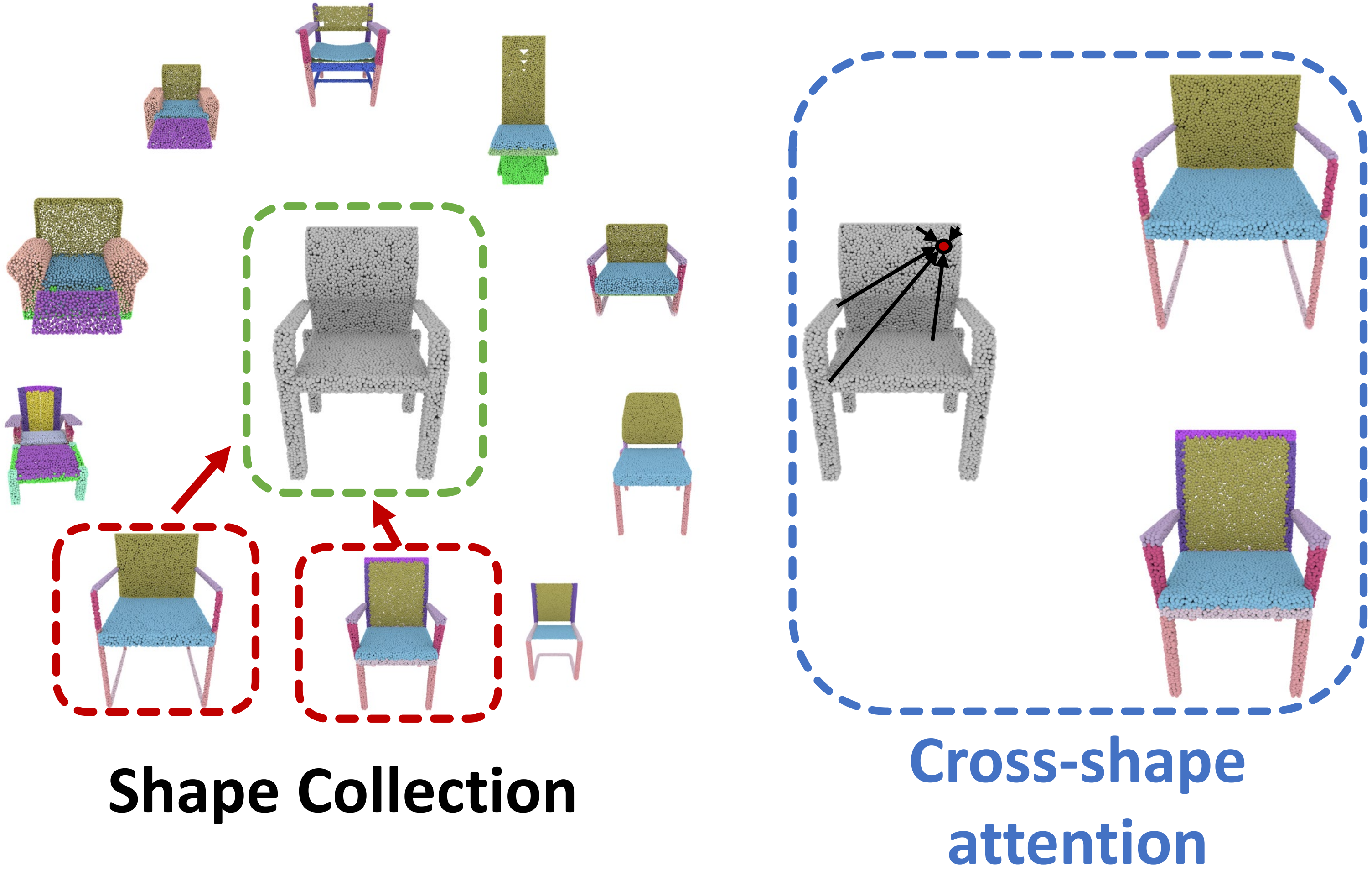

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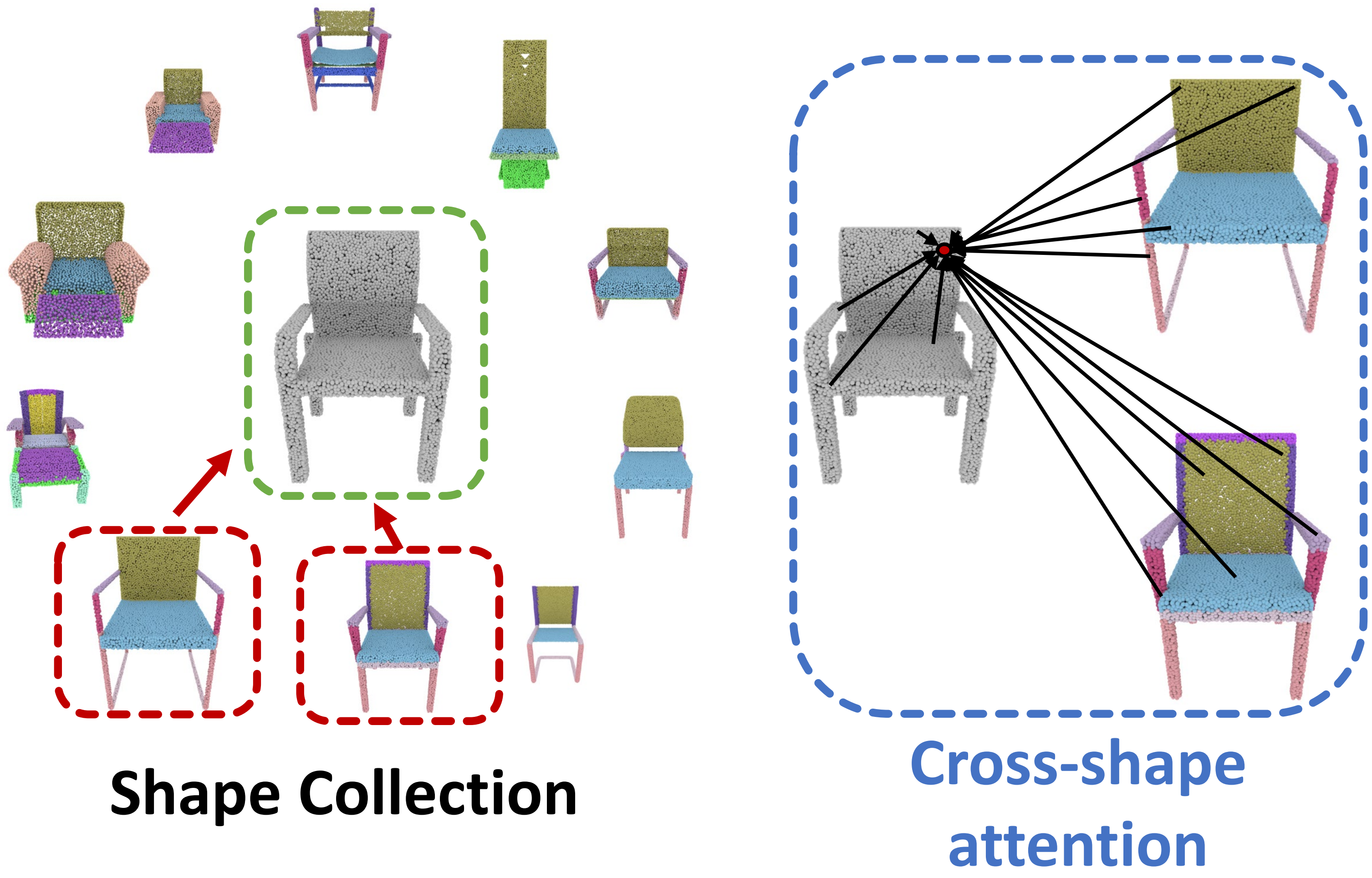

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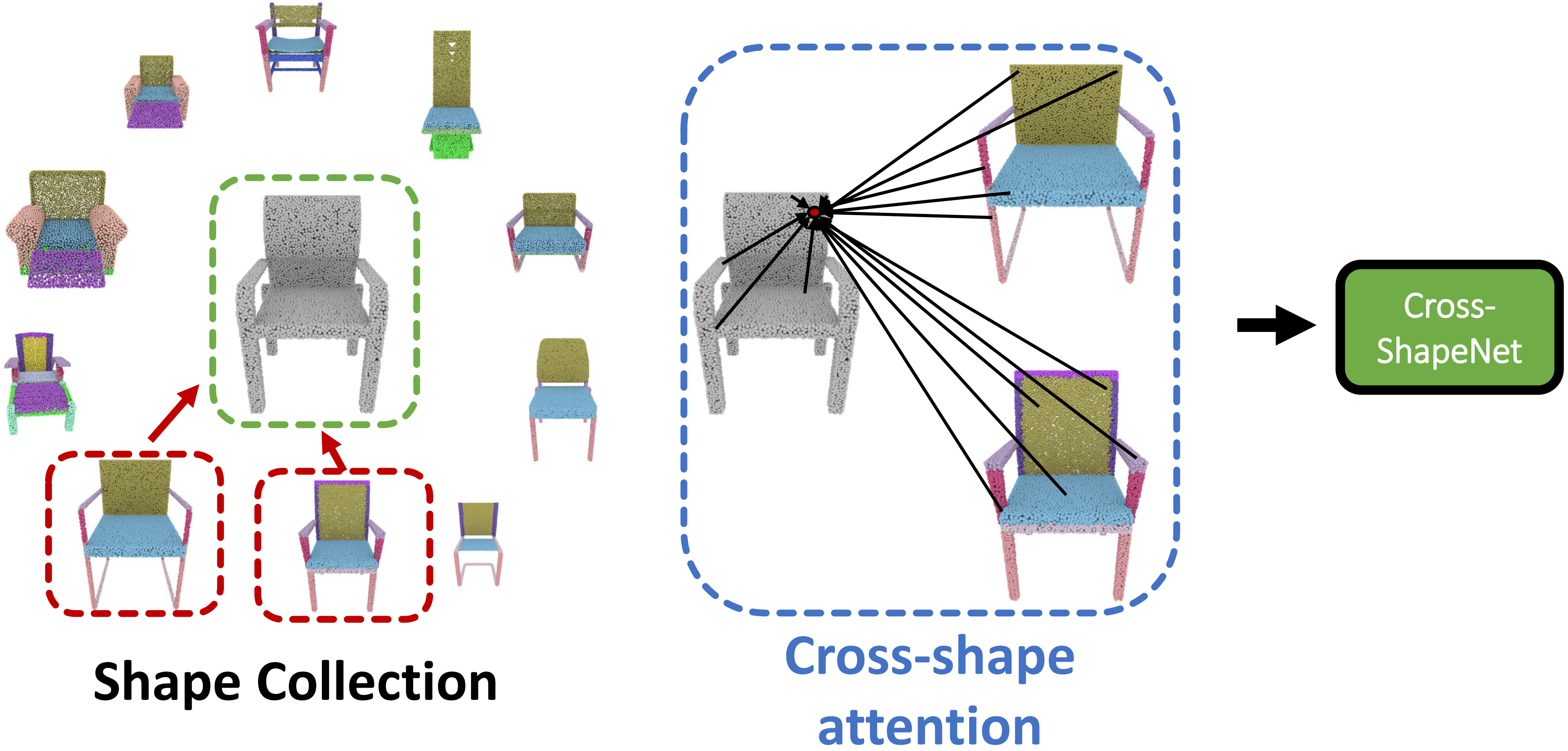
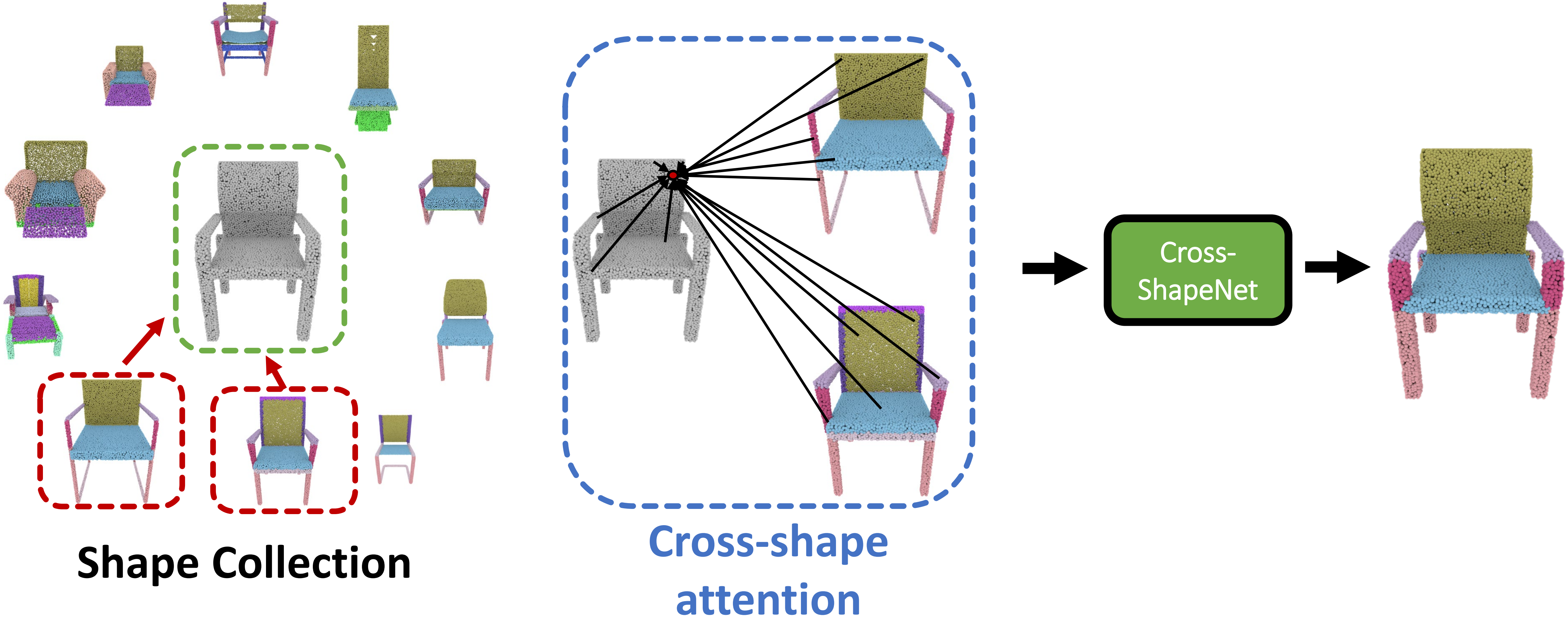
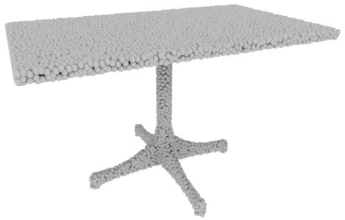


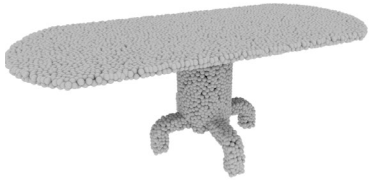
Pipeline



Cross-Shape Attention

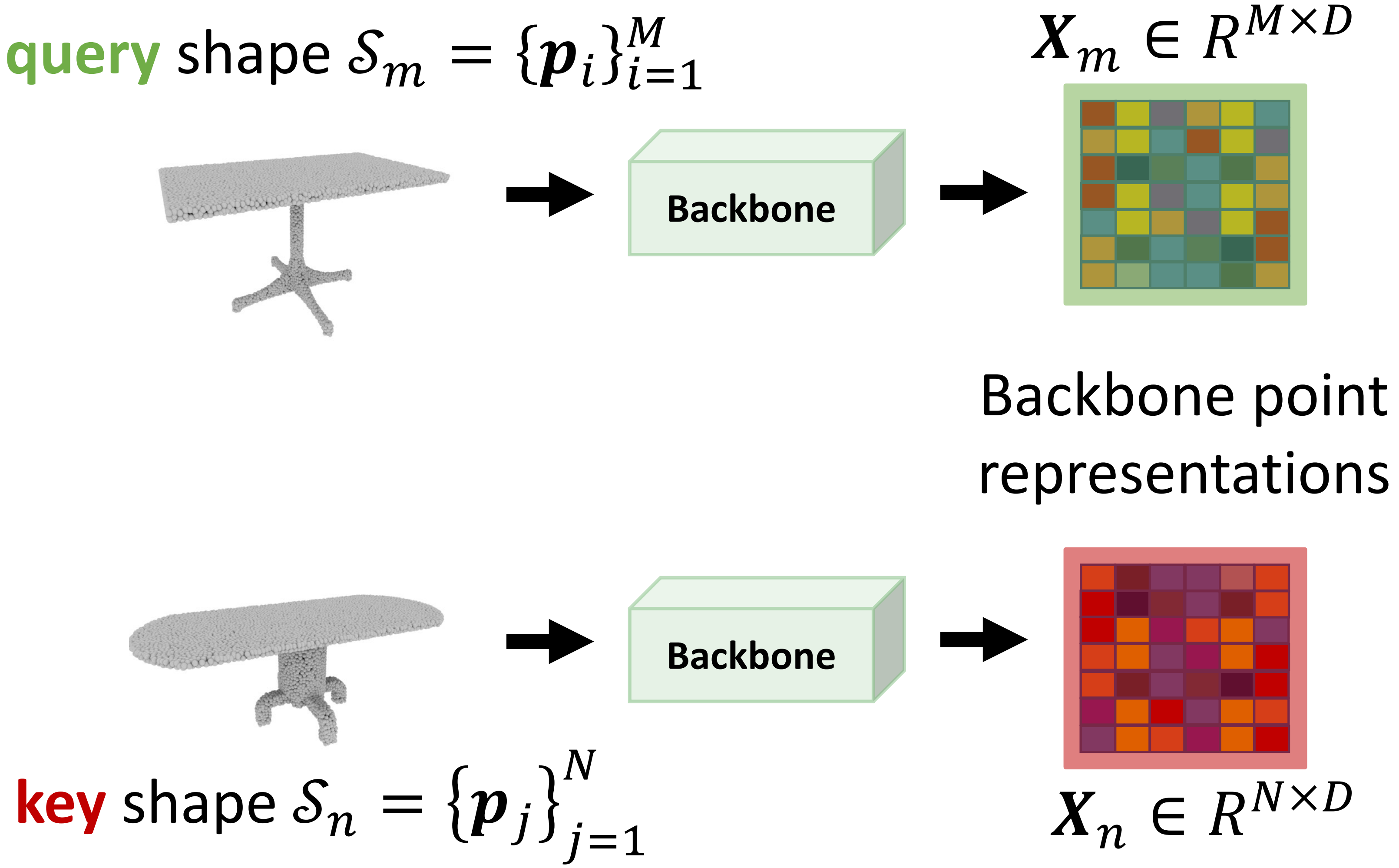
query shape $\mathcal{S}_m = \{\boldsymbol{p}_i\}_{i=1}^{M}$





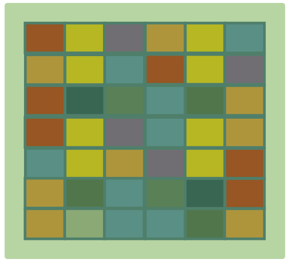
key shape $\mathcal{S}_n = \{\boldsymbol{p}_j\}_{j=1}^{N}$

Cross-Shape Attention

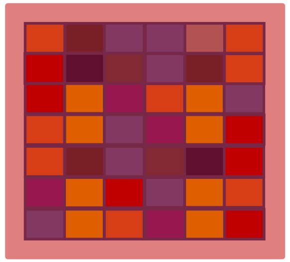


Cross-Shape Attention

$\boldsymbol{X}_m \in R^{M \times D}$



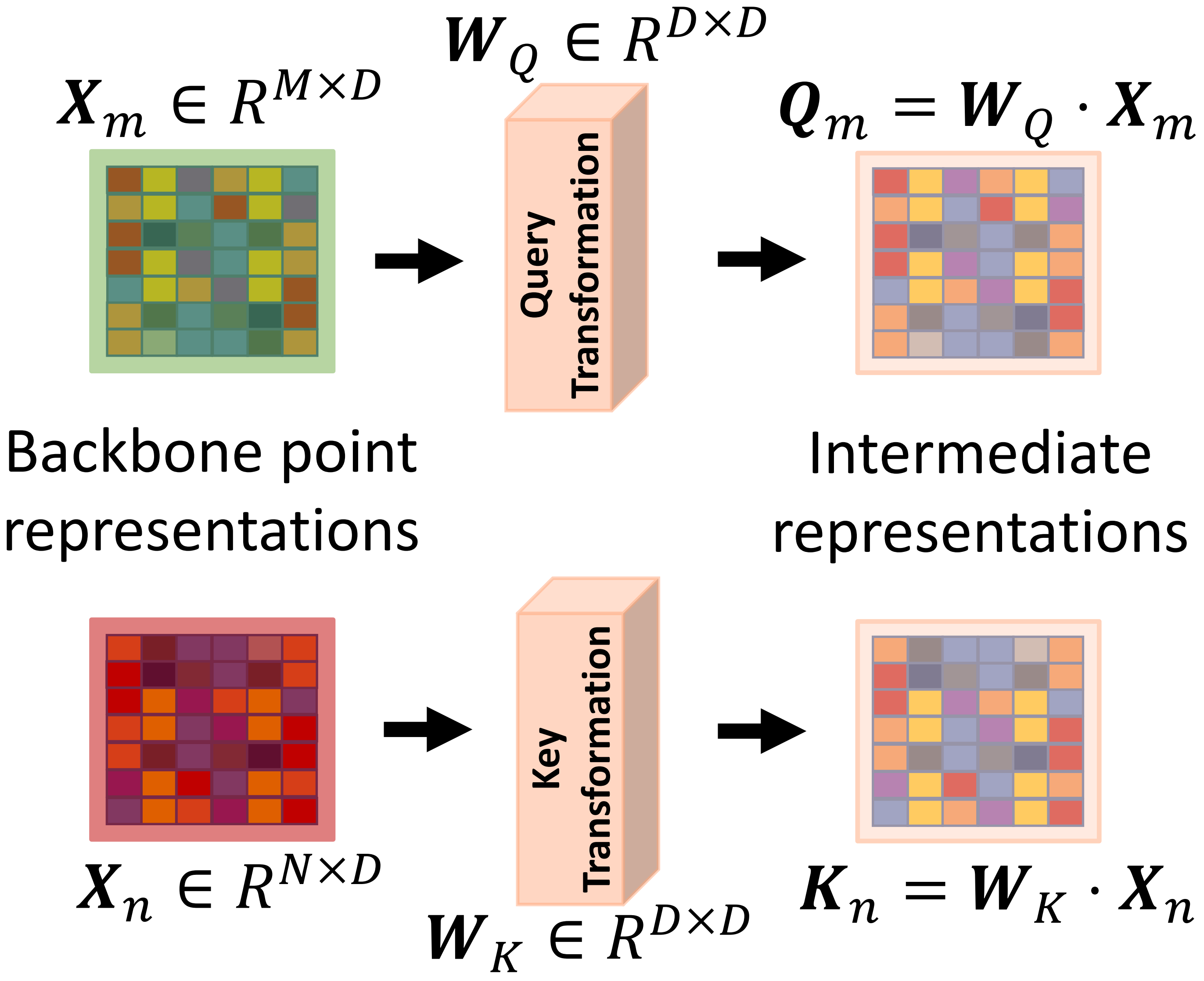
Backbone point representations



$\boldsymbol{X}_n \in R^{N \times D}$

Transformer [Vaswani et al. 2017]

Cross-Shape Attention



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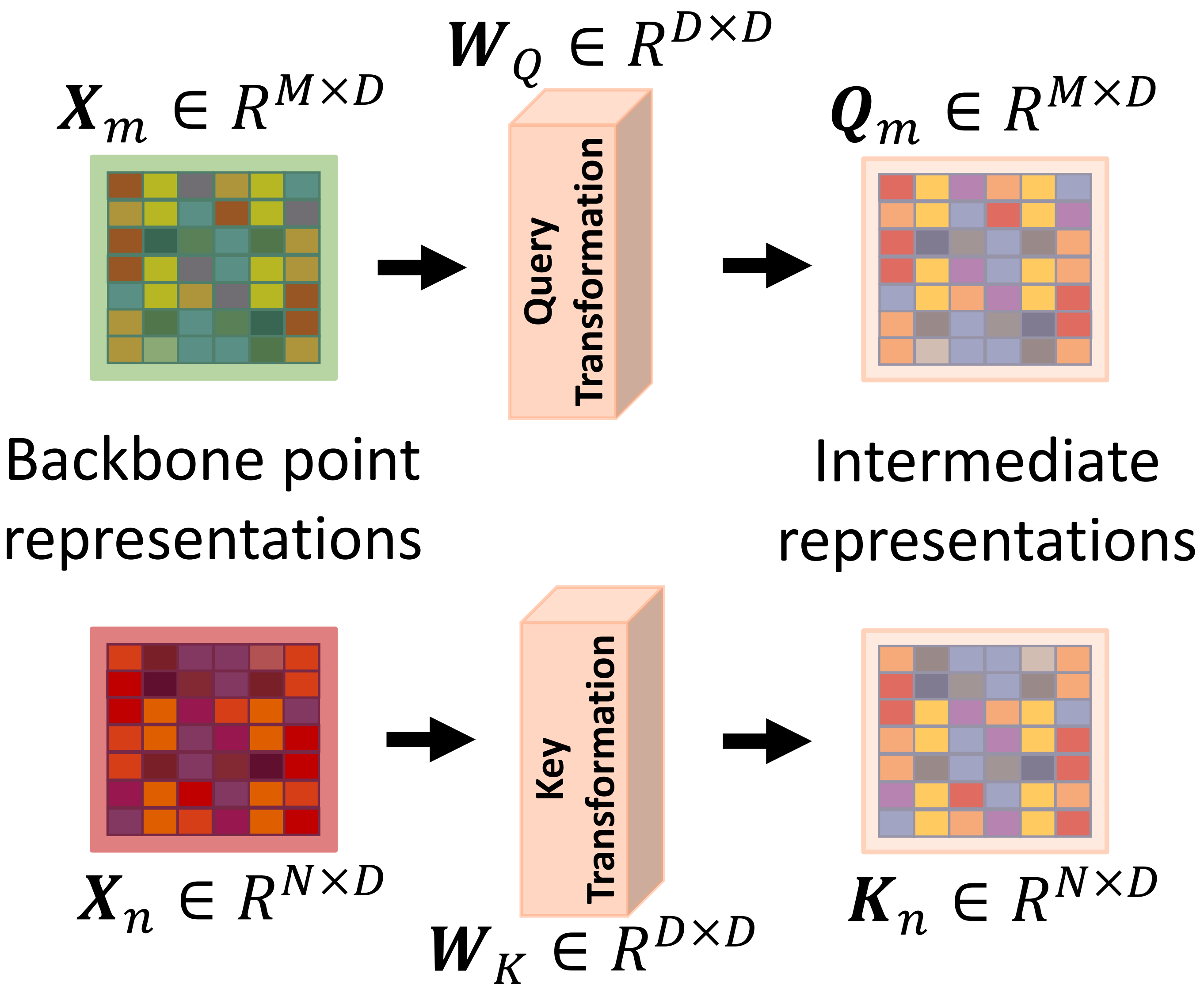

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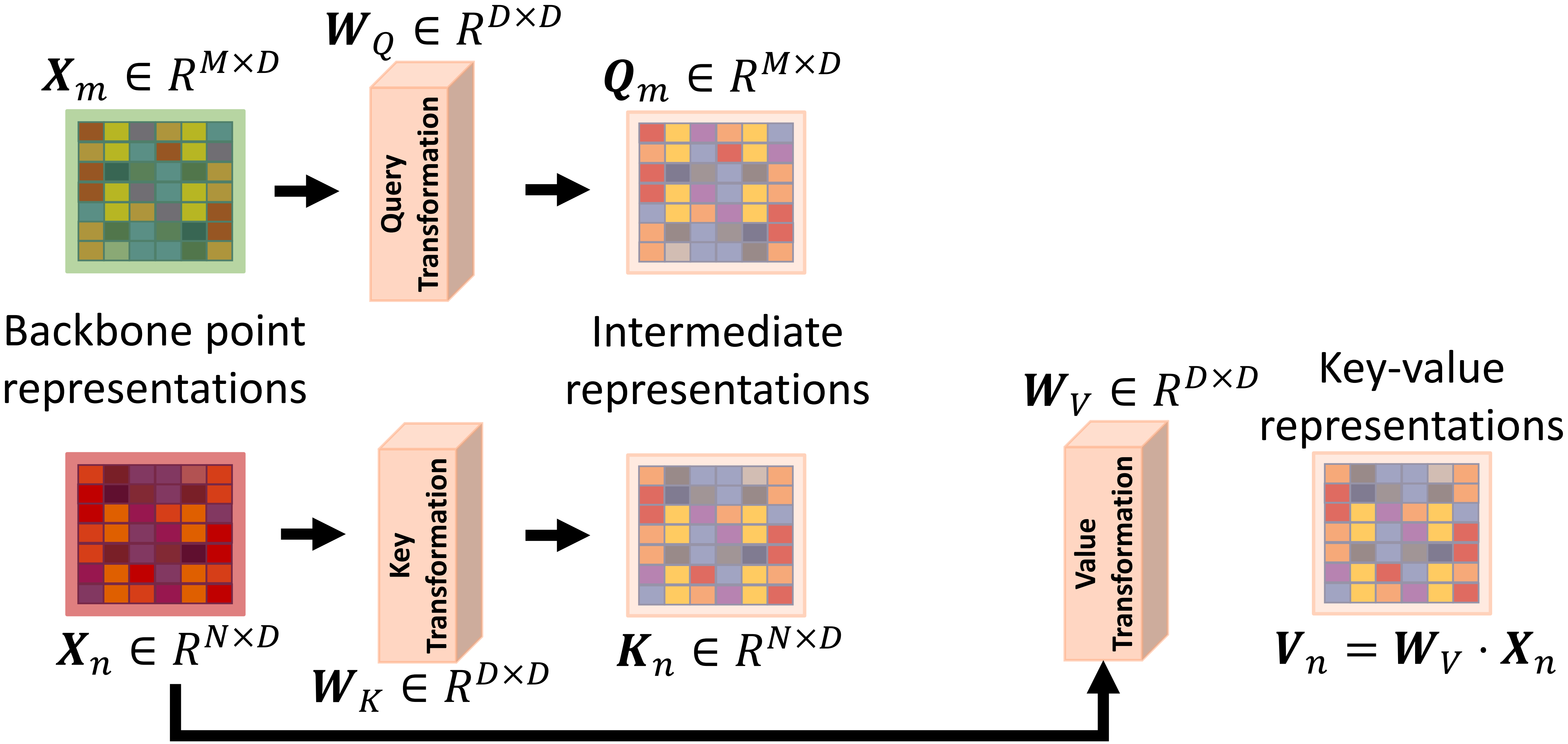

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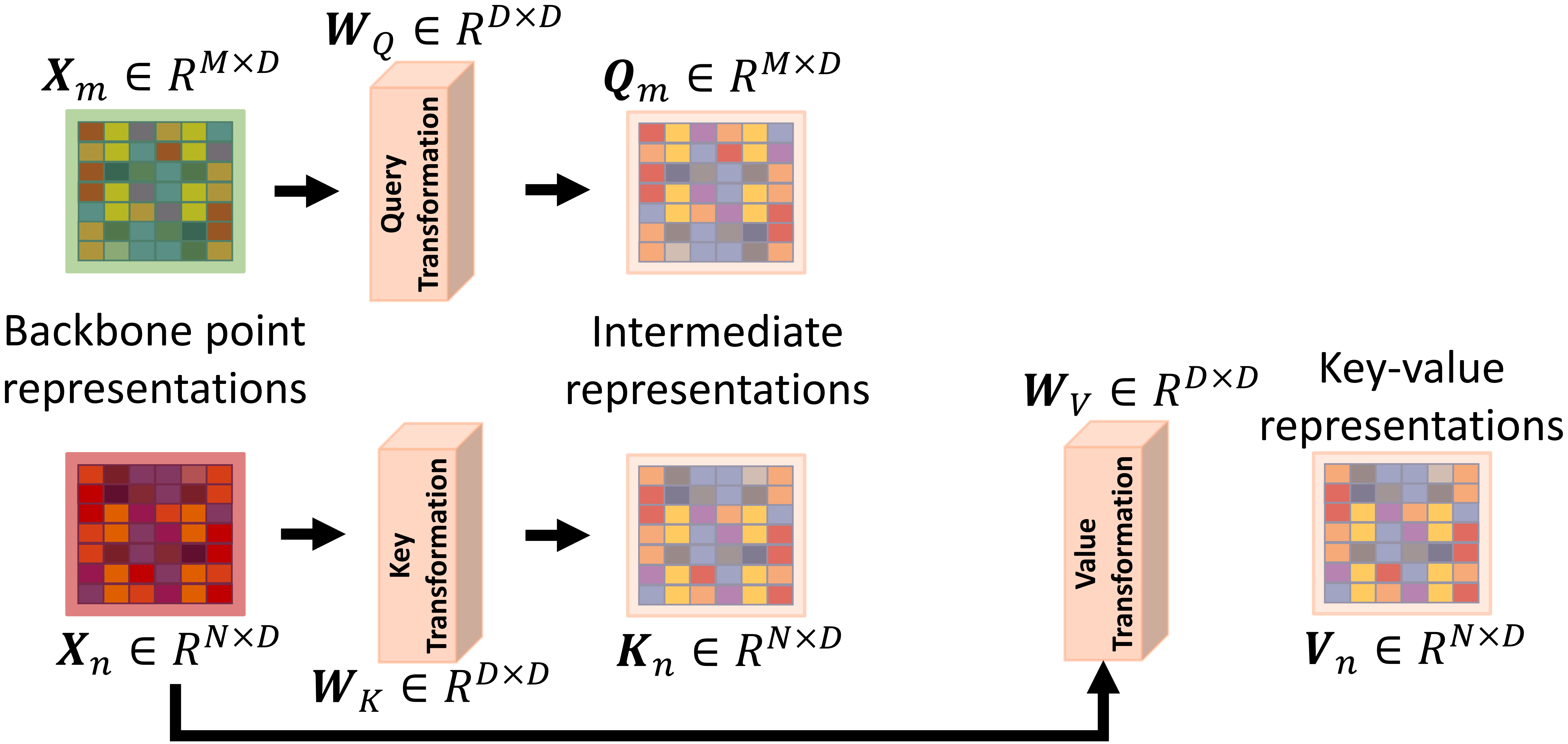


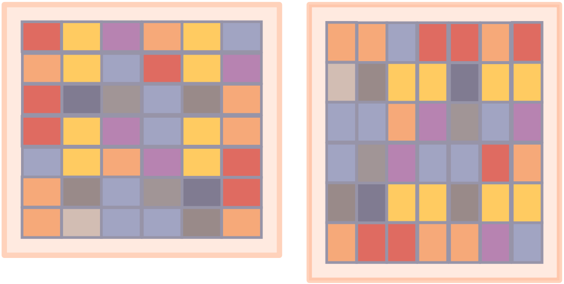
Transformer [Vaswani et al. 2017]

Cross-Shape Attention

Query representations

Key representations

$\boldsymbol{Q}_m$ $\mathbf{K}_n^T$

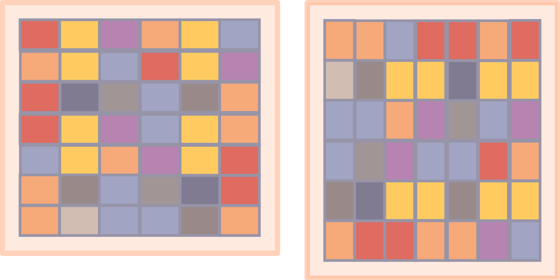


Transformer [Vaswani et al. 2017]

Cross-Shape Attention

Query representations | Key representations

$$\boldsymbol{Q}_m \qquad \mathbf{K}_n^T$$



$$\sqrt{D}$$

$$\boldsymbol{Q}_m \in R^{M \times D}$$
$$\boldsymbol{K}_n \in R^{N \times D}$$

Transformer [Vaswani et al. 2017]

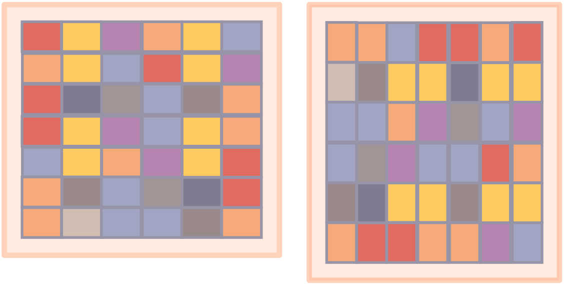
Cross-Shape Attention

Query representations | Key representations

$\boldsymbol{Q}_m \quad \mathbf{K}_n^T$

$\boldsymbol{Q}_m \in R^{M \times D}$

$\boldsymbol{K}_n \in R^{N \times D}$



$\sqrt{D}$

$$Var\left(\frac{\boldsymbol{Q}_{i,:}\boldsymbol{K}^T_{:,j}}{\sqrt{D}}\right) = 1,$$

$$\forall i = 1, \cdots, M$$

$$\forall j = 1, \cdots, N$$

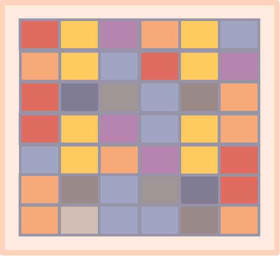
Transformer [Vaswani et al. 2017]

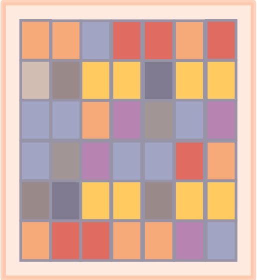
Cross-Shape Attention

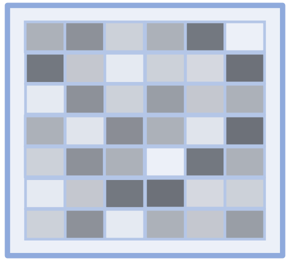
Query representations

Key representations

$$softmax\left(\frac{\boldsymbol{Q}_m \mathbf{K}_n^T}{\sqrt{D}}\right) = \boldsymbol{A}_{m,n} \in R^{M\times N}$$





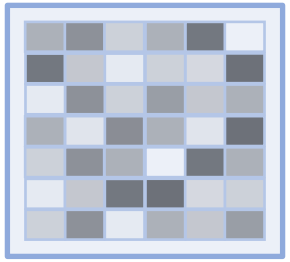


Attention matrix

Transformer [Vaswani et al. 2017]

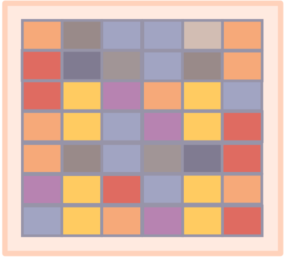
Cross-Shape Attention

$\boldsymbol{A}_{m,n}$



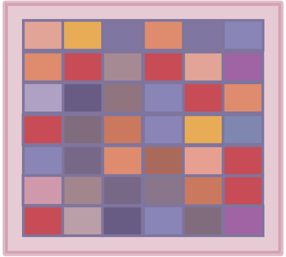
$\cdot$

$\boldsymbol{V}_n$



$=$

$\boldsymbol{X'}^{(CSA)}_m \in R^{M \times D}$



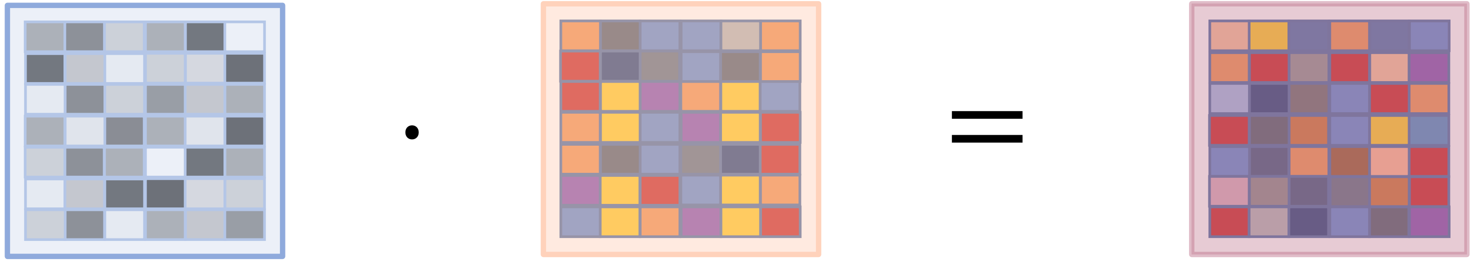
Cross-shape attention matrix

Key shape value representations

Cross-shape attention representations

Cross-Shape Attention

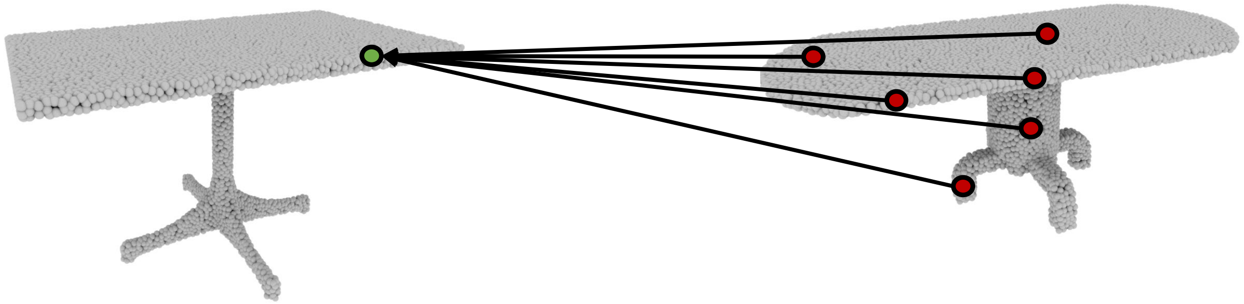
$$\boldsymbol{A}_{m,n} \cdot \boldsymbol{V}_n = \boldsymbol{X}'^{(CSA)}_m \in R^{M \times D}$$



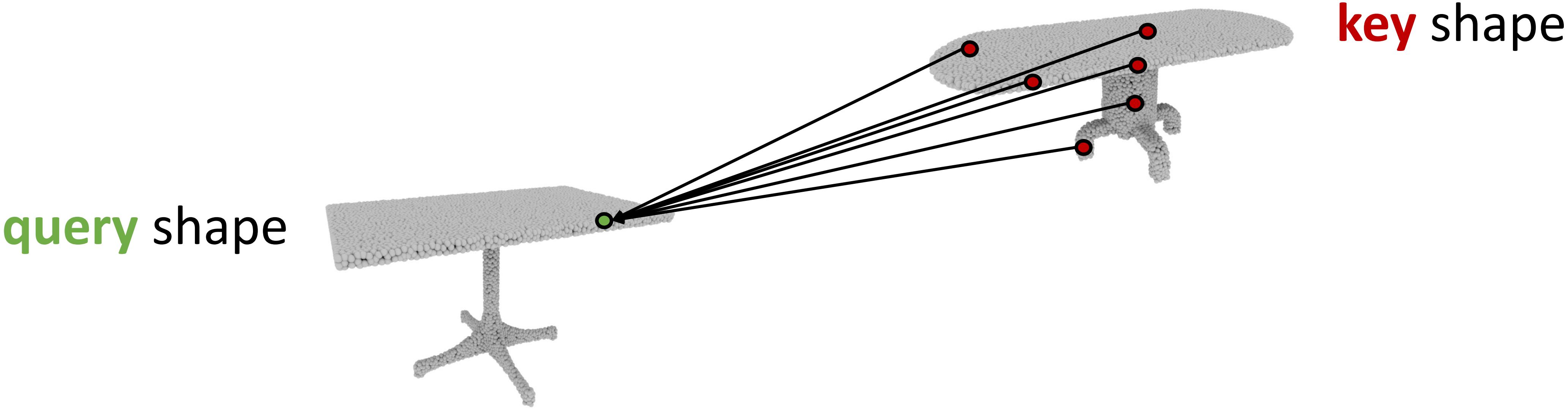
Cross-shape attention matrix

Key shape value representations

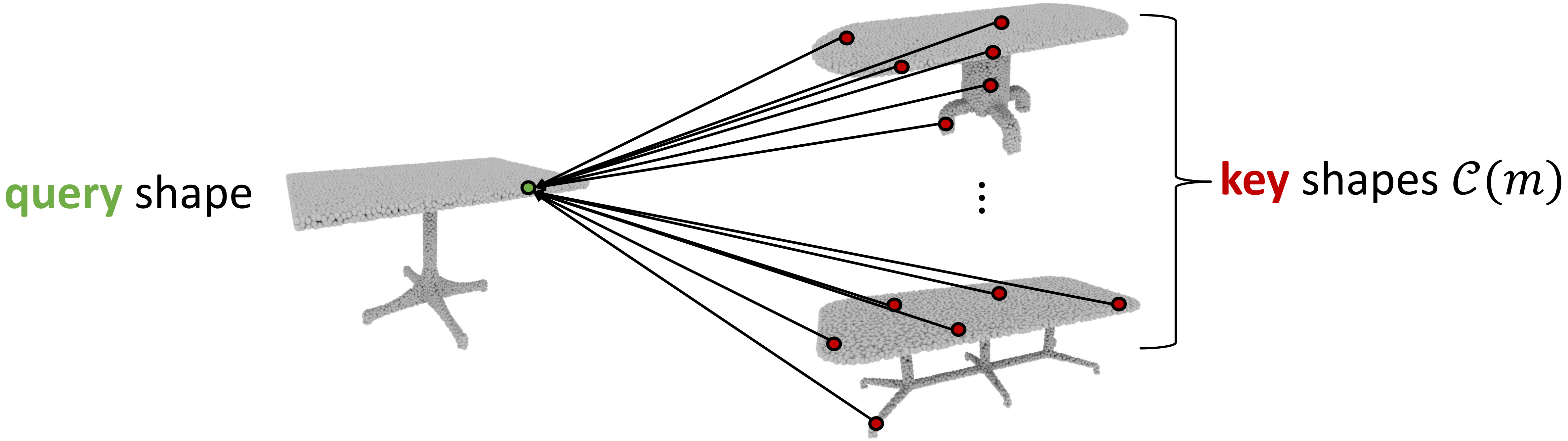
Cross-shape attention representations



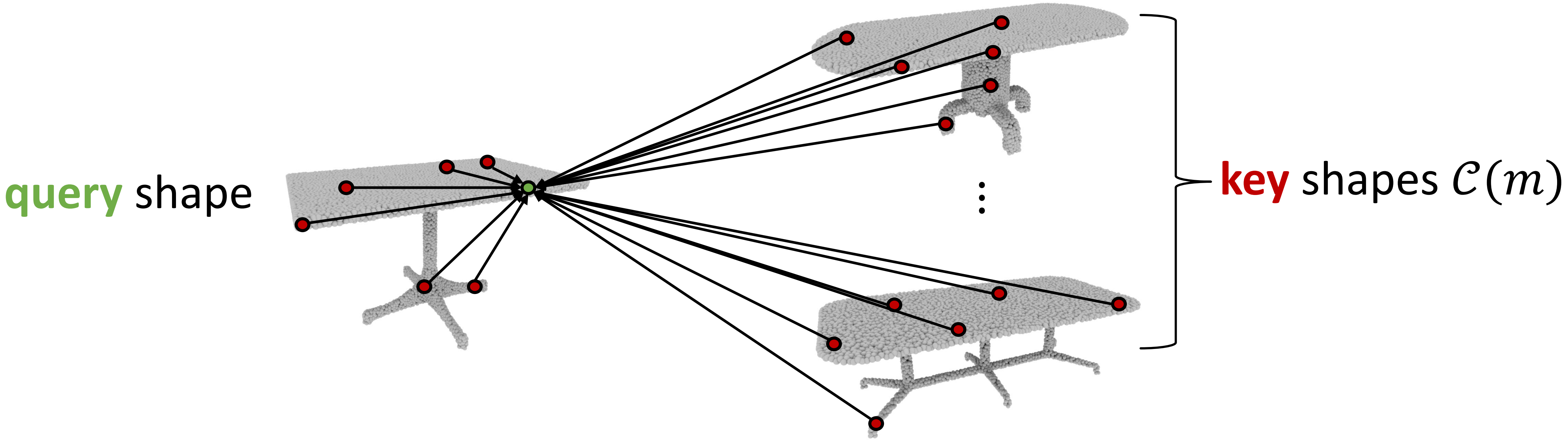
Cross-Shape Attention for multiple shapes



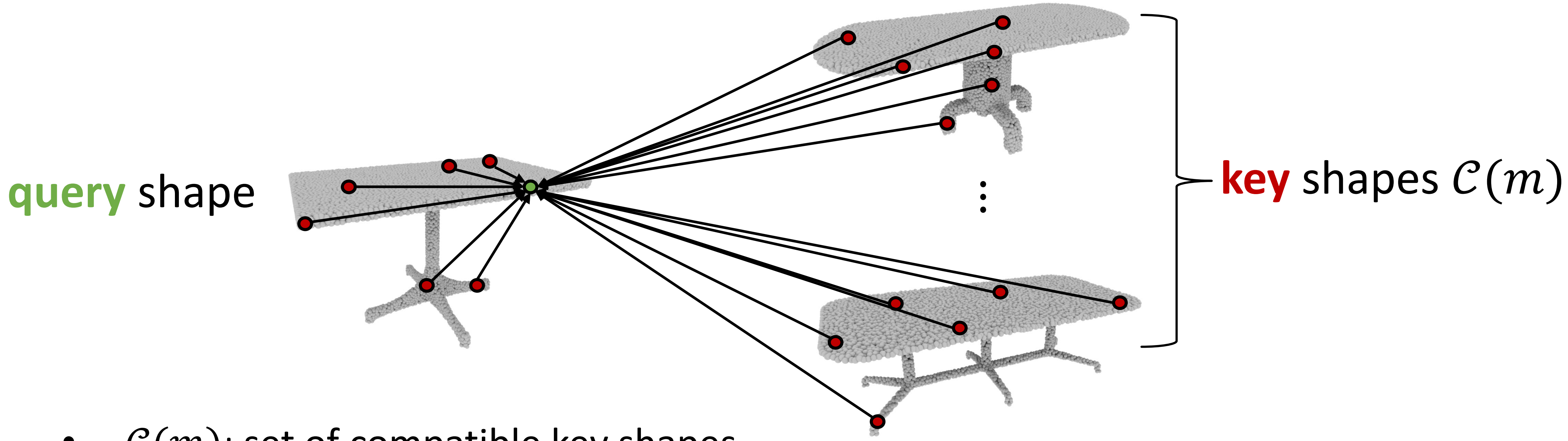
Cross-Shape Attention for multiple shapes



Cross-Shape Attention for multiple shapes



Cross-Shape Attention for multiple shapes



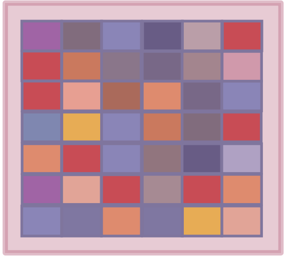
- $\mathcal{C}(m)$: set of compatible key shapes
- $c(m,n)$: compatibility function between query shape S_m and key shape S_n

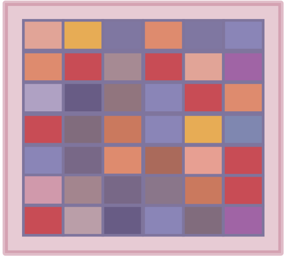
Cross-shape attention output

$$\boldsymbol{X}'_m = \sum_{n \in \{\mathcal{C}(m), m\}} c(m,n)\boldsymbol{A}_{m,n}\boldsymbol{V}_n$$

Compatibility function

$\boldsymbol{X'}_m^{(SSA)} \in R^{M \times D}$

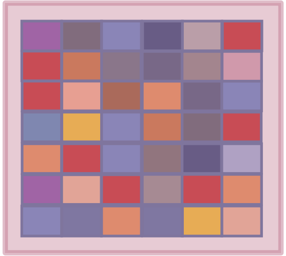




$\boldsymbol{X'}_n^{(SSA)} \in R^{N \times D}$

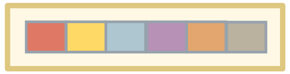
Compatibility function

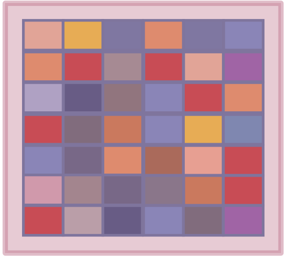
$\boldsymbol{X'}_m^{(SSA)} \in R^{M \times D}$



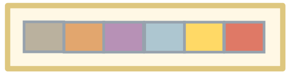
$\operatorname*{avg}_i \boldsymbol{X'}_{m,i}^{(SSA)}$

$\boldsymbol{y}_m^{(SSA)} \in R^{D}$





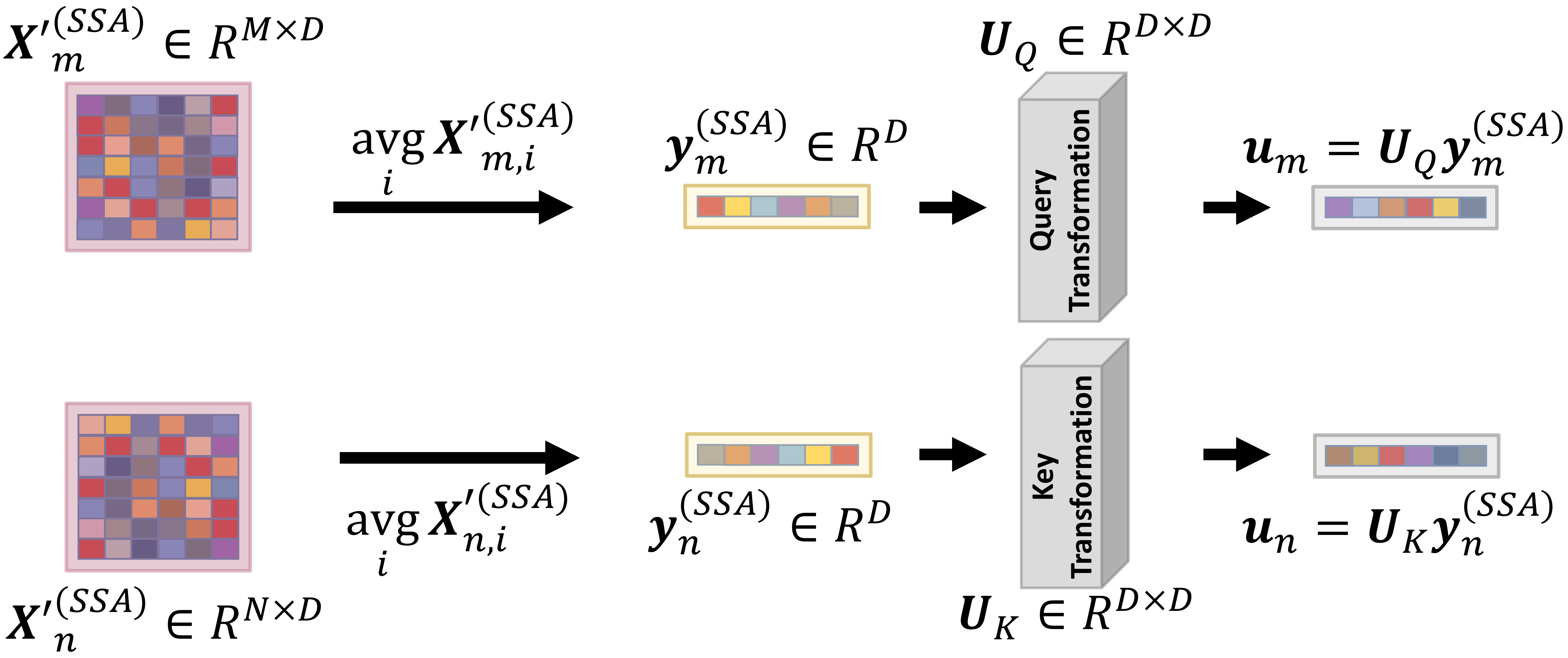
$\operatorname*{avg}_i \boldsymbol{X'}_{n,i}^{(SSA)}$



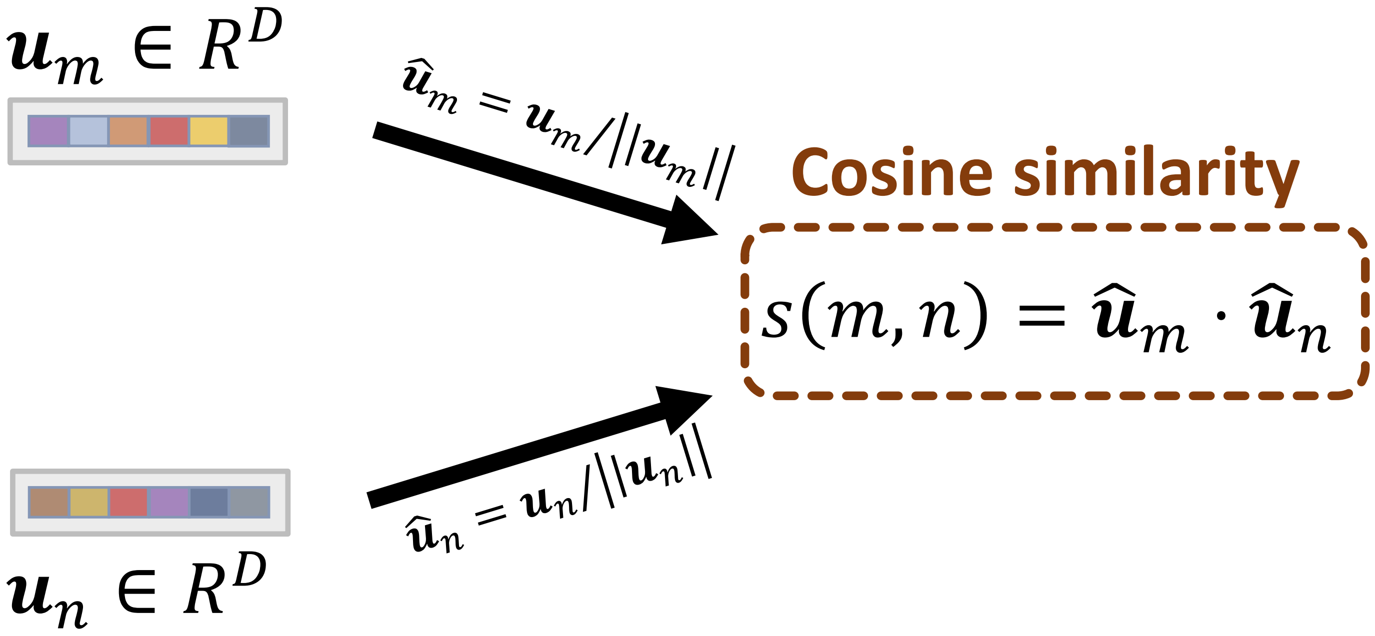
$\boldsymbol{y}_n^{(SSA)} \in R^{D}$

$\boldsymbol{X'}_n^{(SSA)} \in R^{N \times D}$

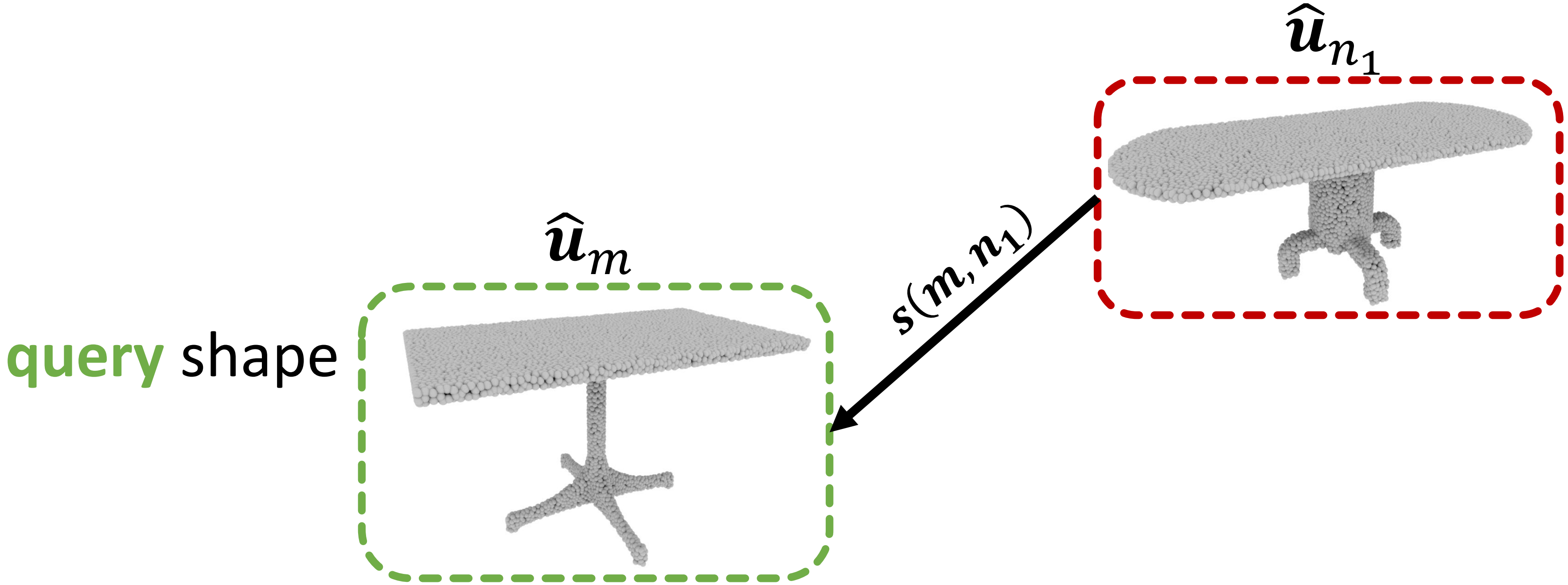
Compatibility function



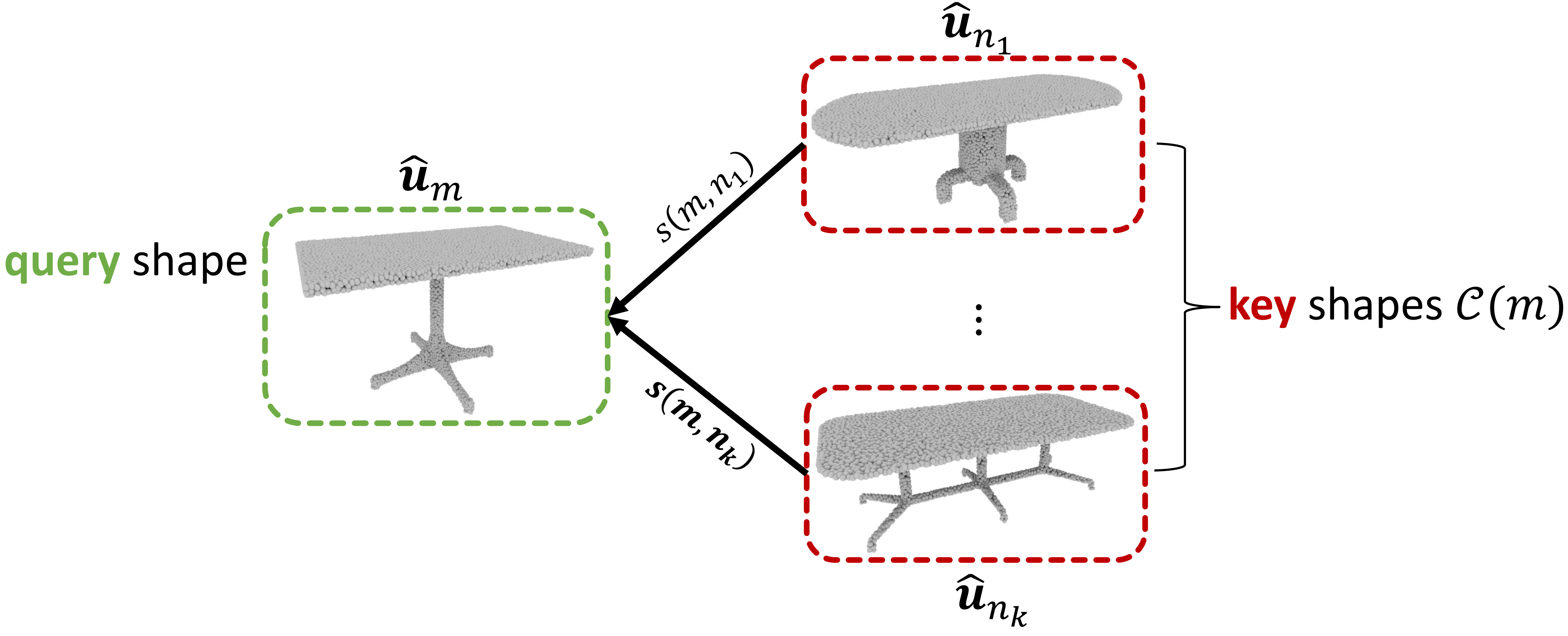
Compatibility function



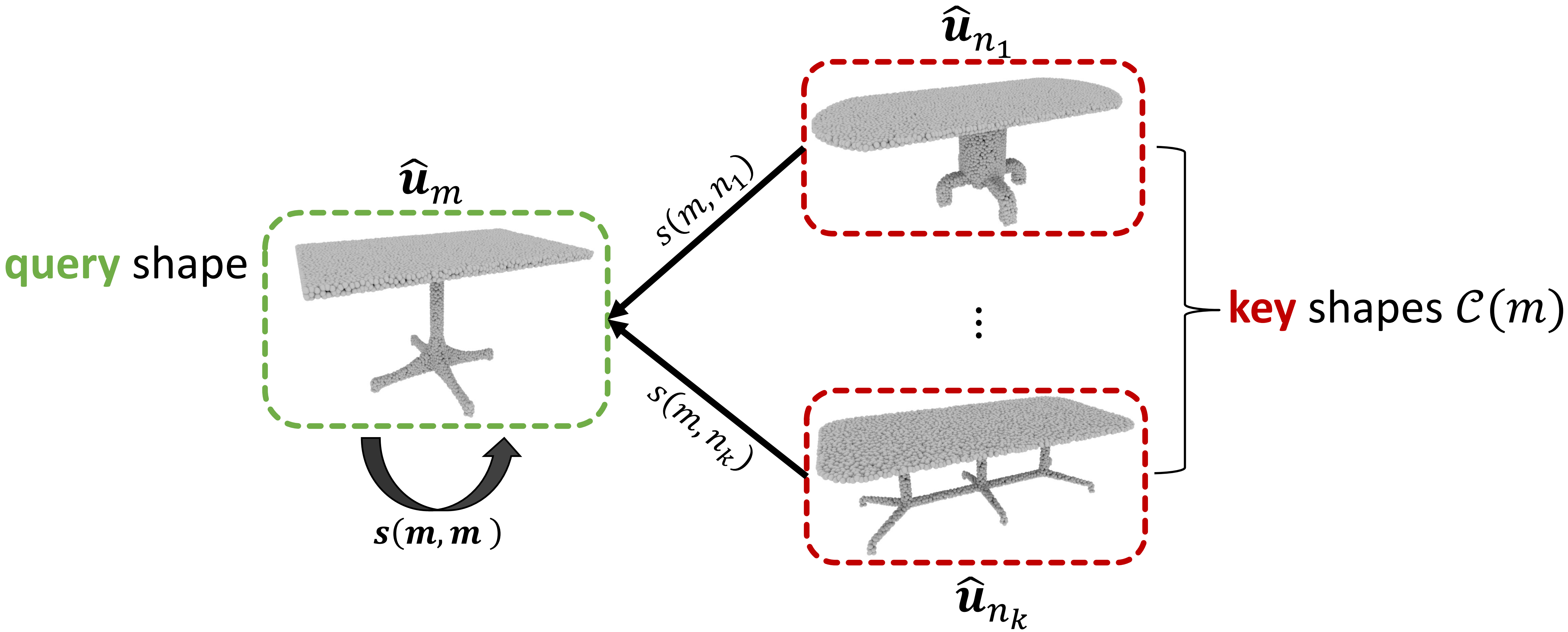
Compatibility function



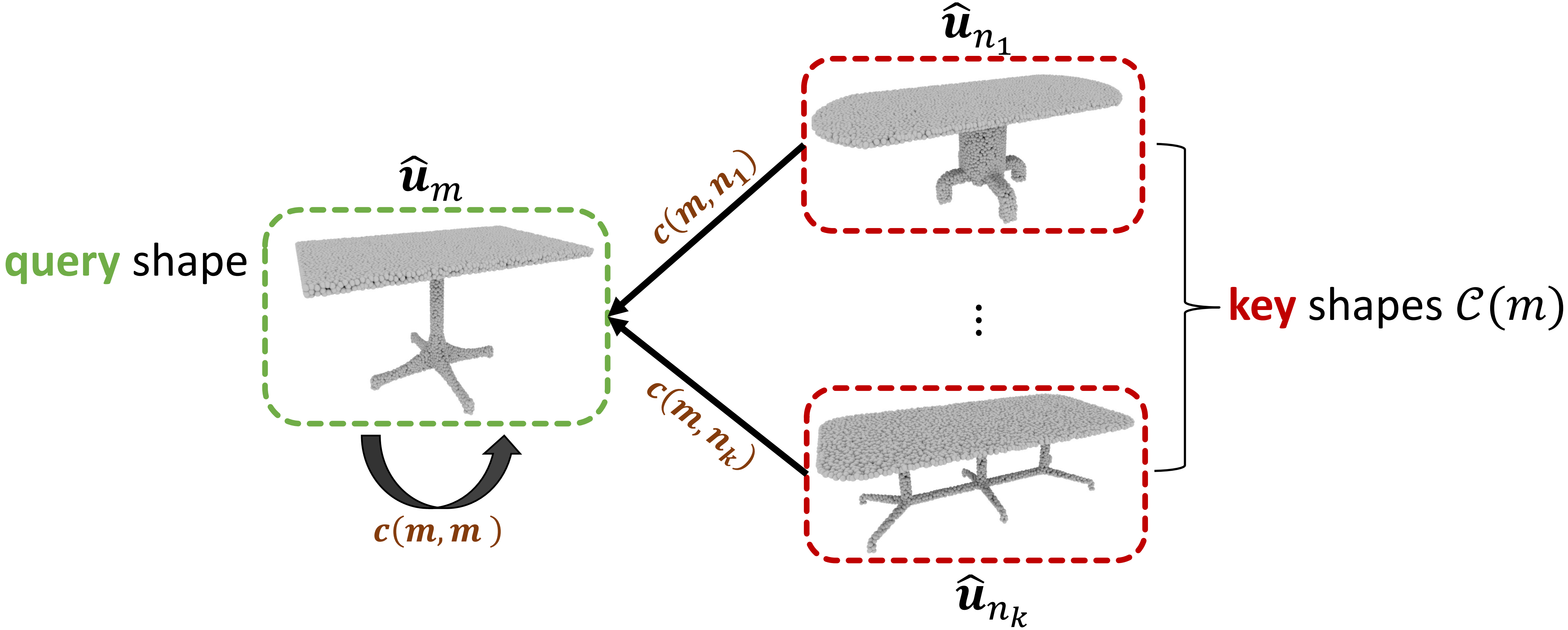
Compatibility function



Compatibility function

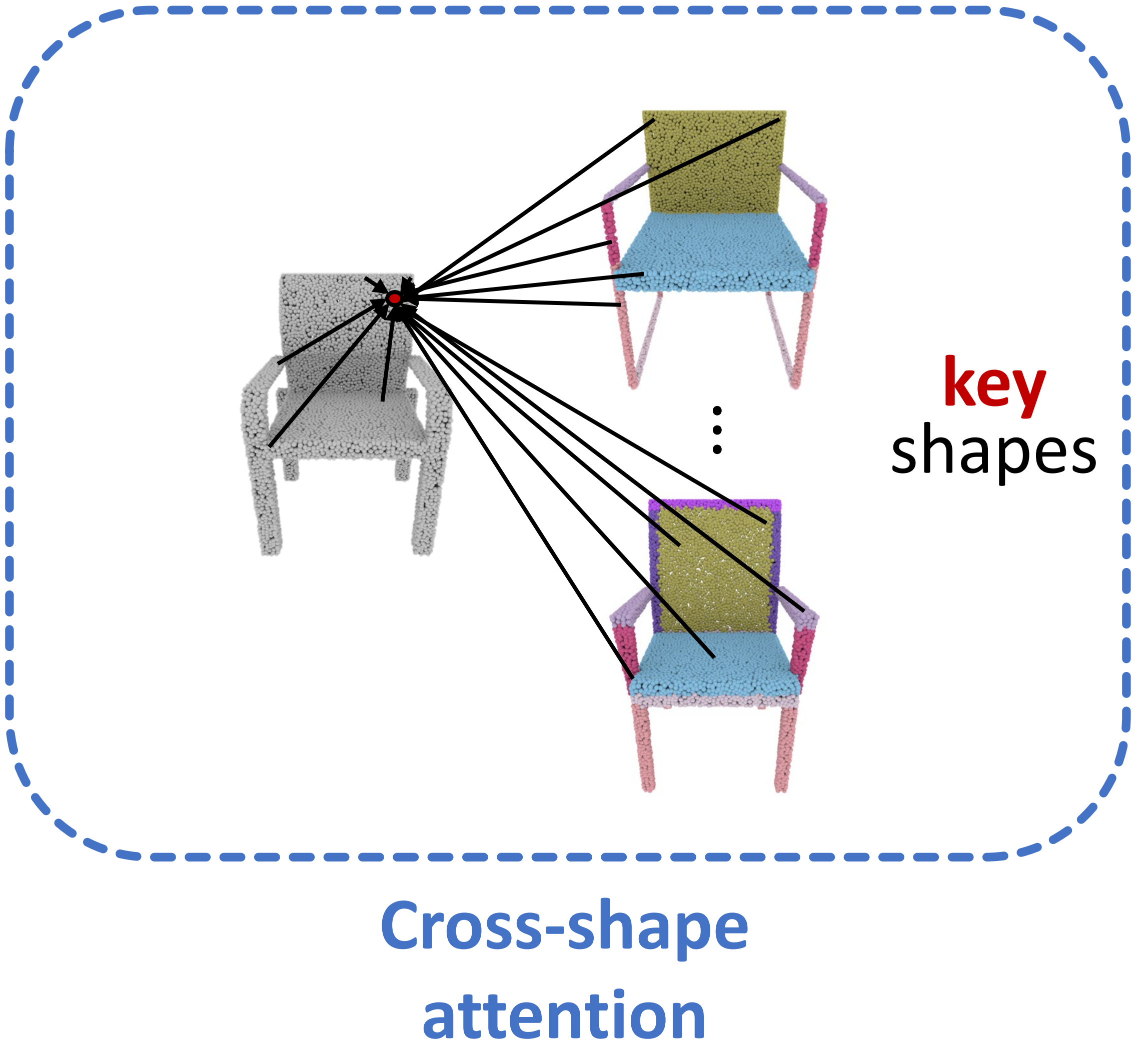


Compatibility function

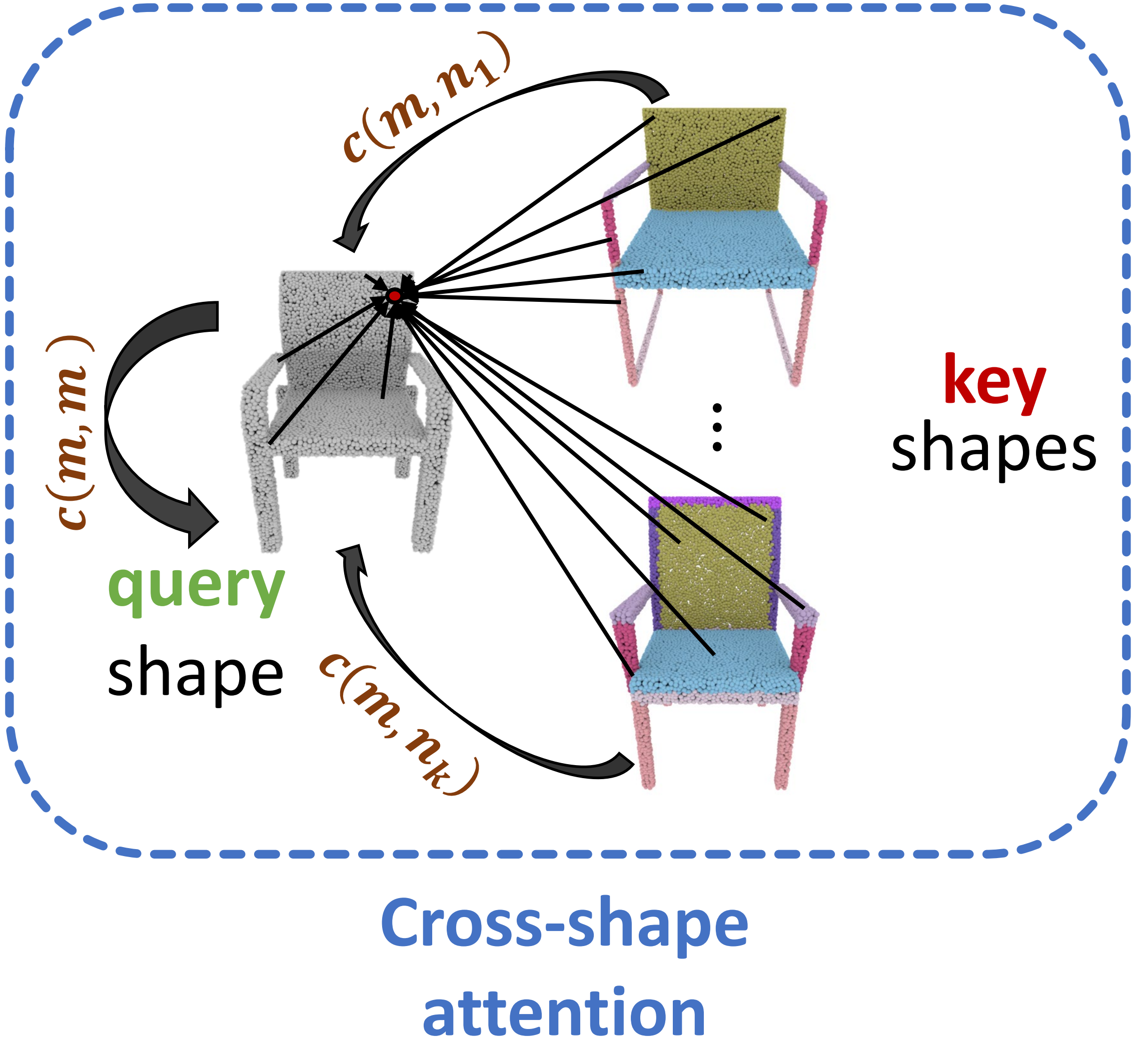


compatibility $c(m,n) = \dfrac{e^{s(m,n)}}{\sum_{n \in \{\mathcal{C}(m), m\}} e^{s(m,n)}}$

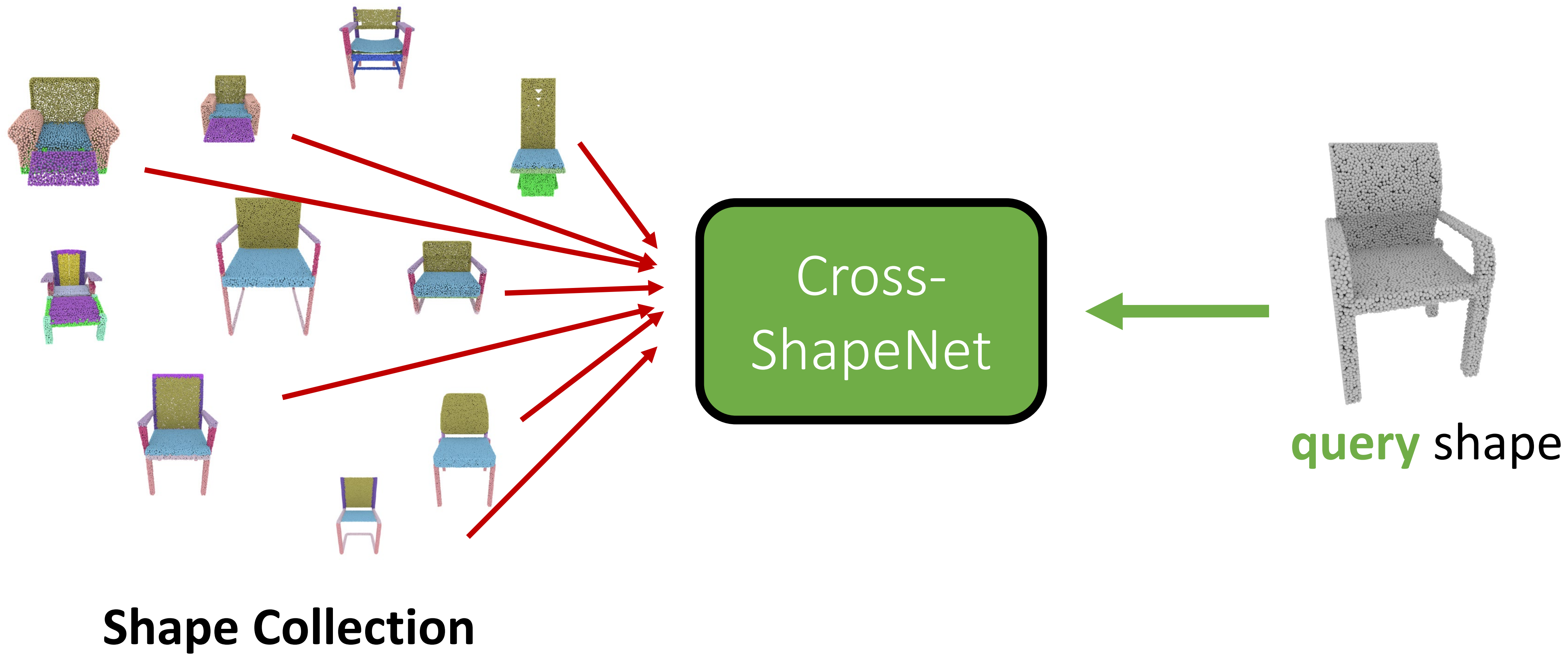
Cross-Shape Attention for multiple shapes



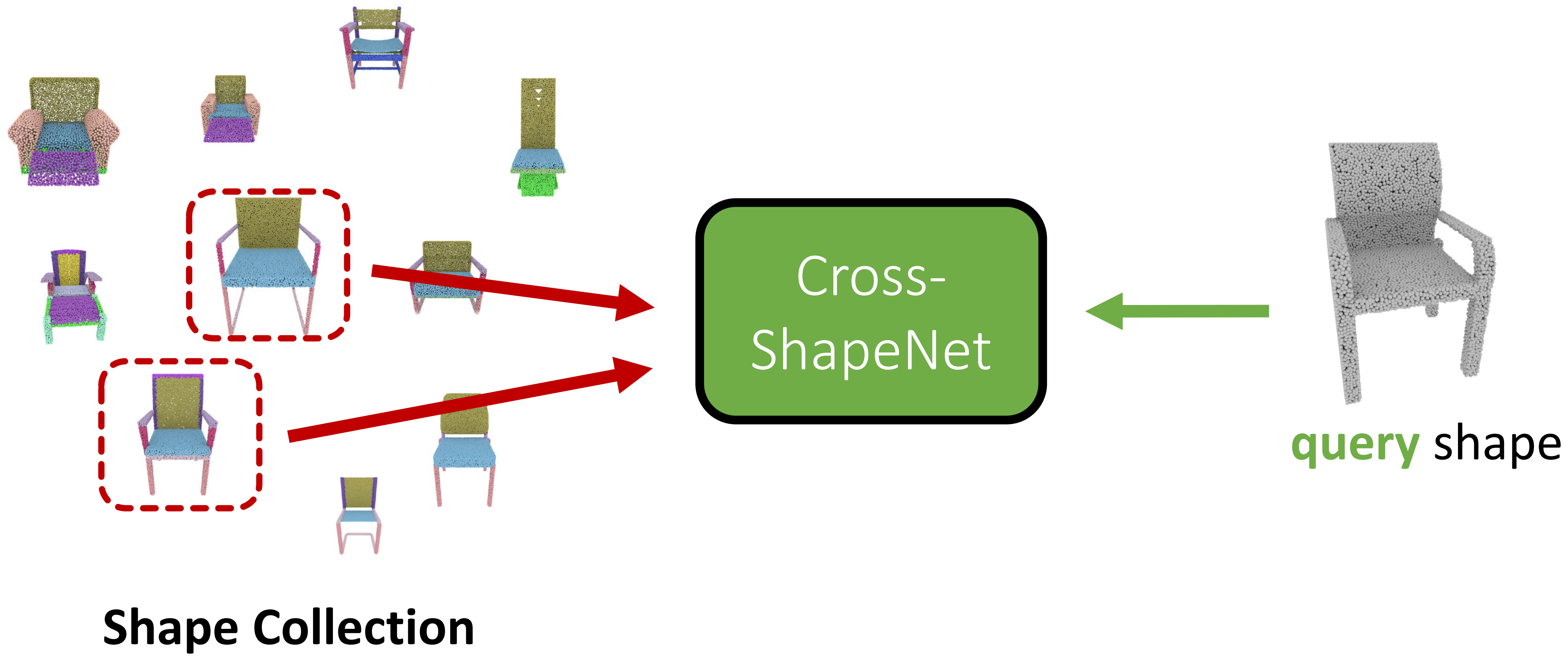
Cross-Shape Attention for multiple shapes



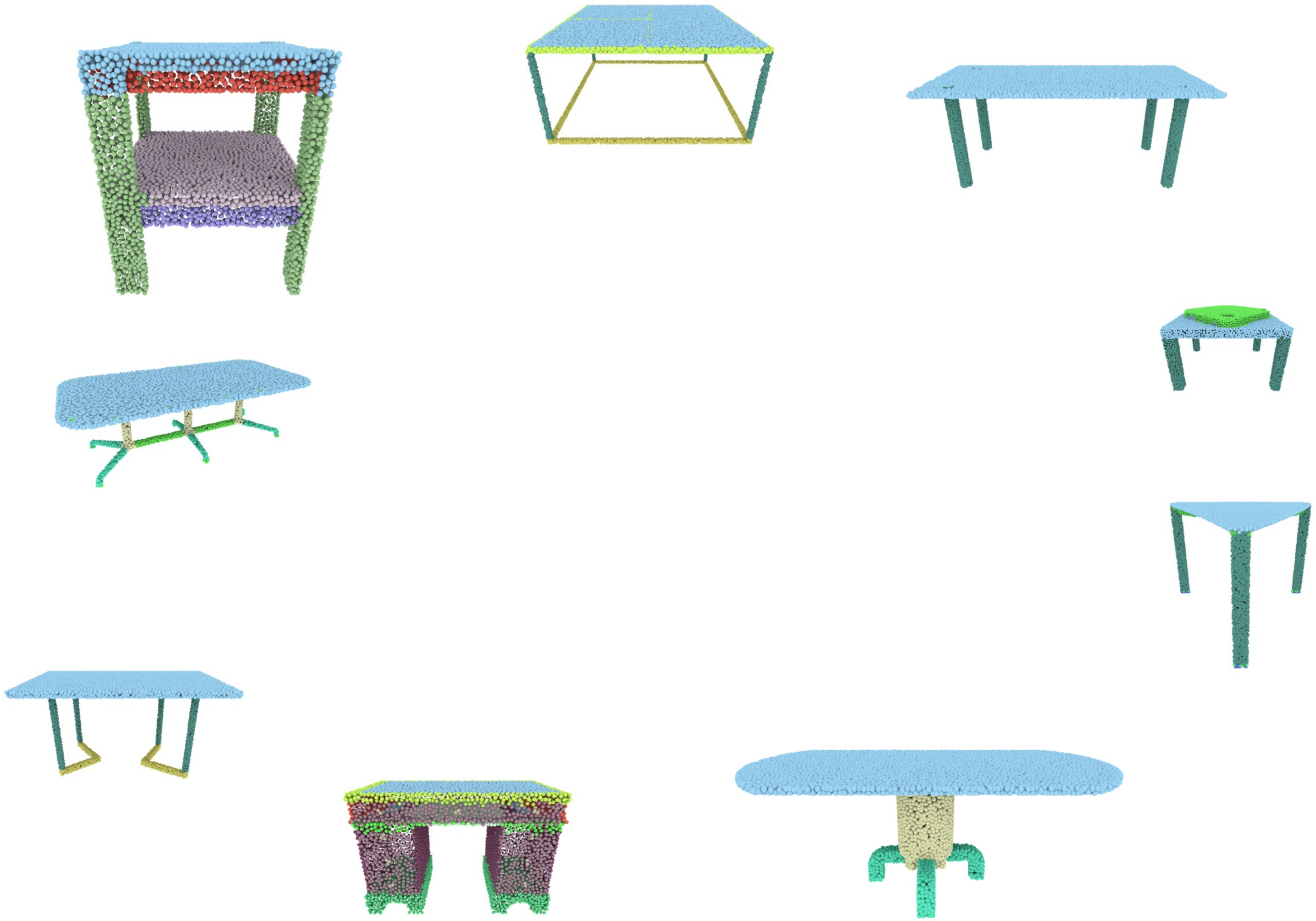
Retrieve compatible shapes



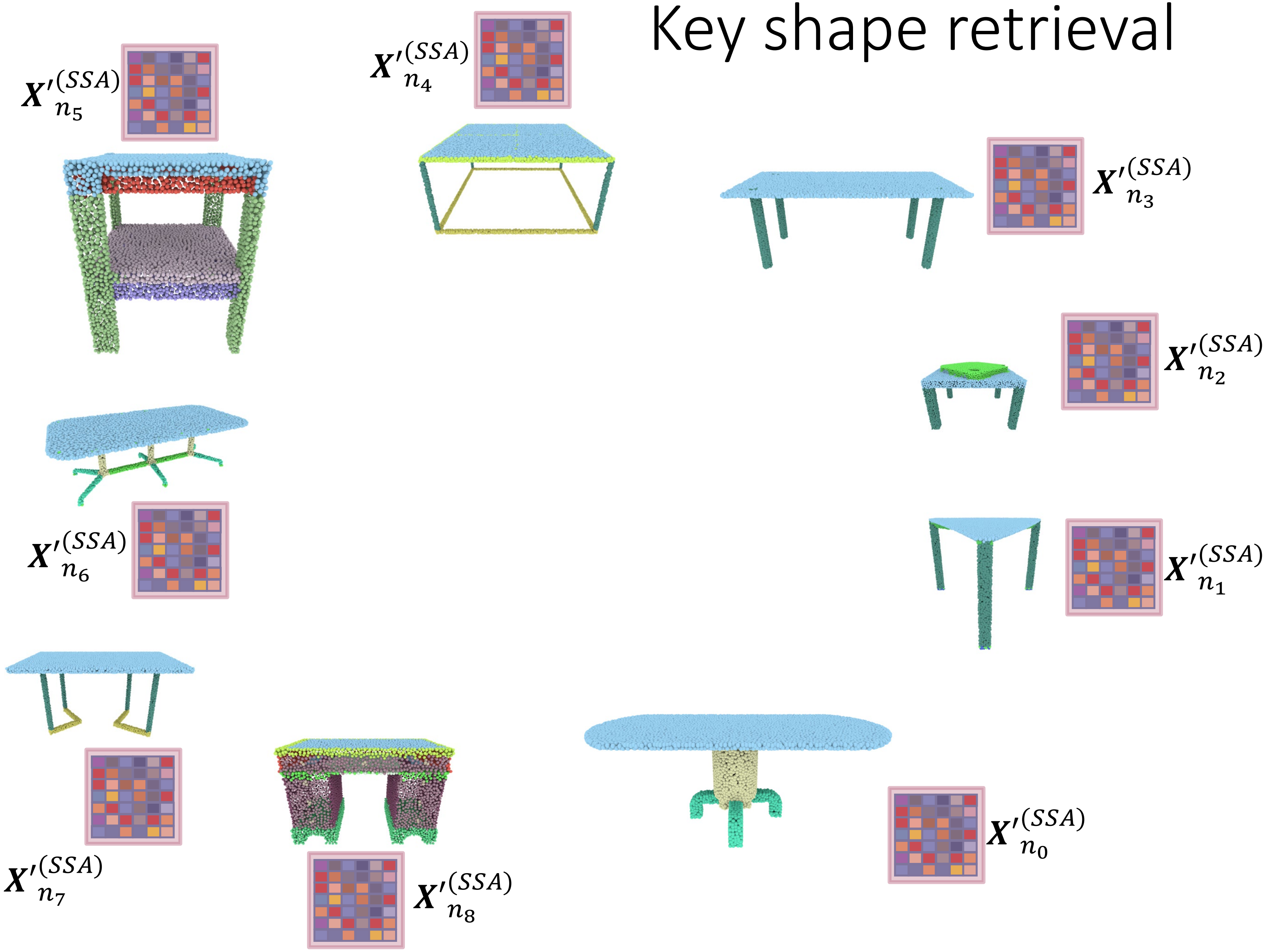
Retrieve compatible shapes



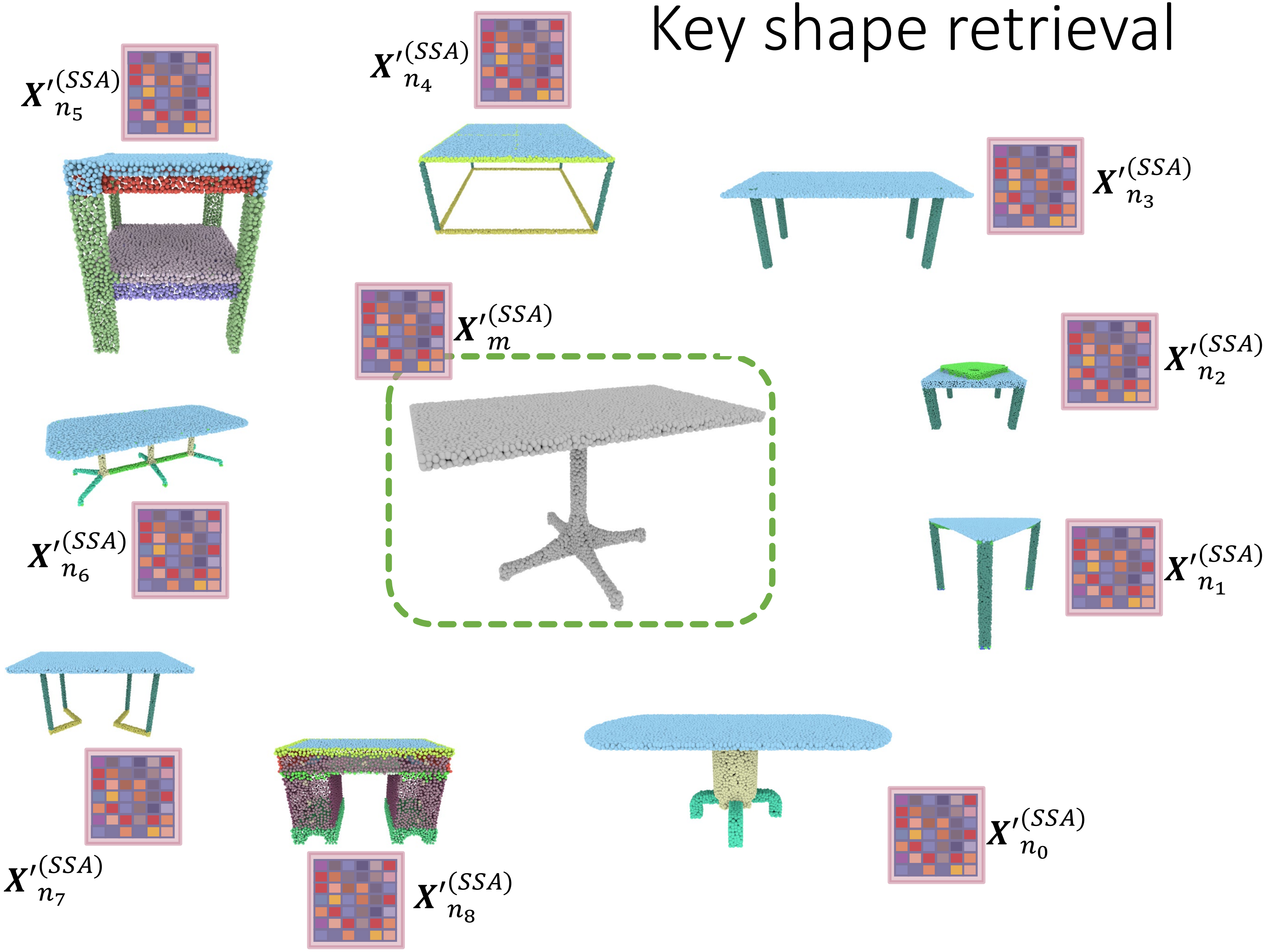
Key shape retrieval



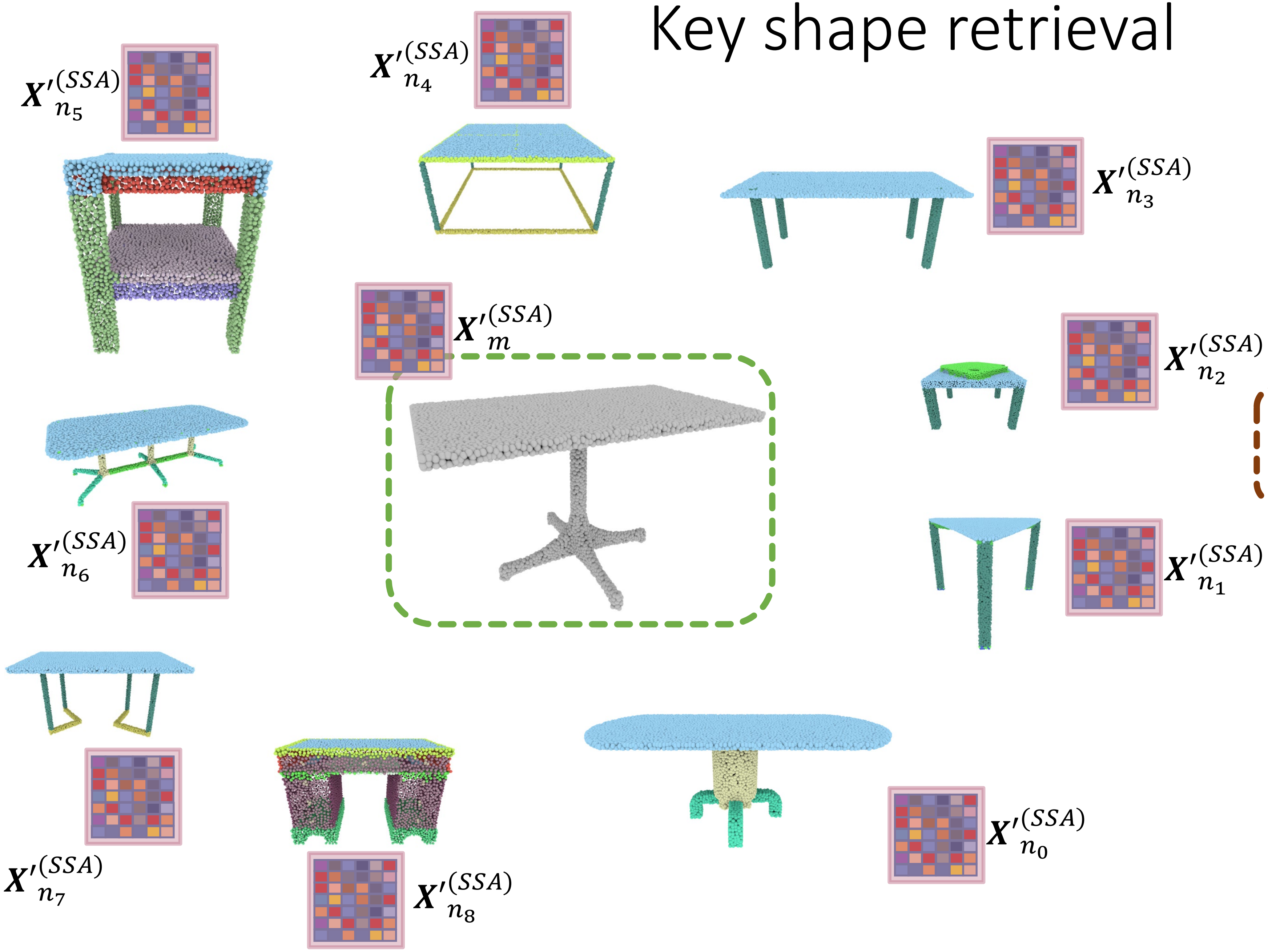
Key shape retrieval



Key shape retrieval



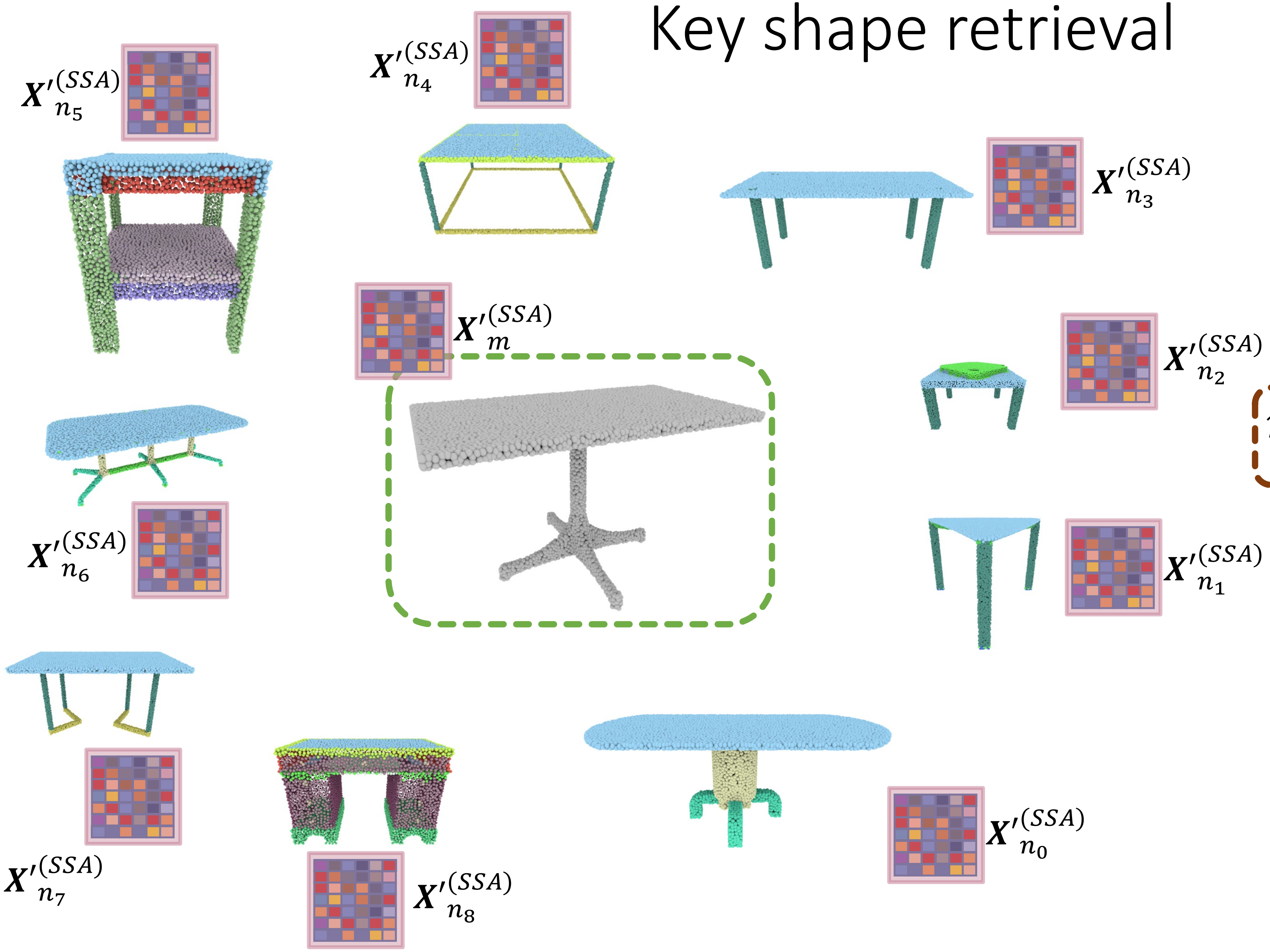
Key shape retrieval



Cosine similarity

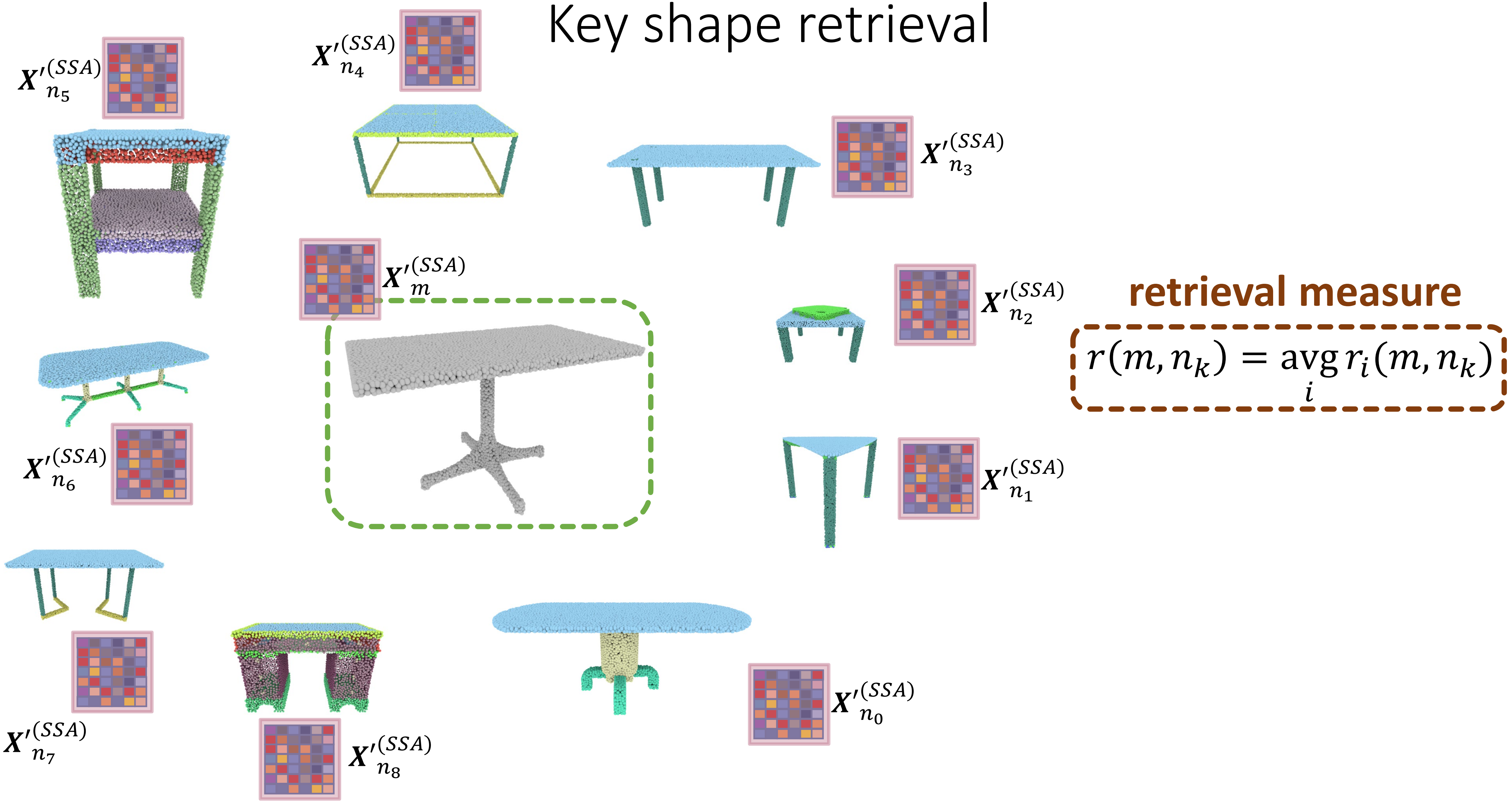
$$\boldsymbol{S}_{m,n_k} = \boldsymbol{X'}^{(SSA)}_{m} \cdot \left(\boldsymbol{X'}^{(SSA)}_{n_k}\right)^{\mathsf{T}}$$

Key shape retrieval

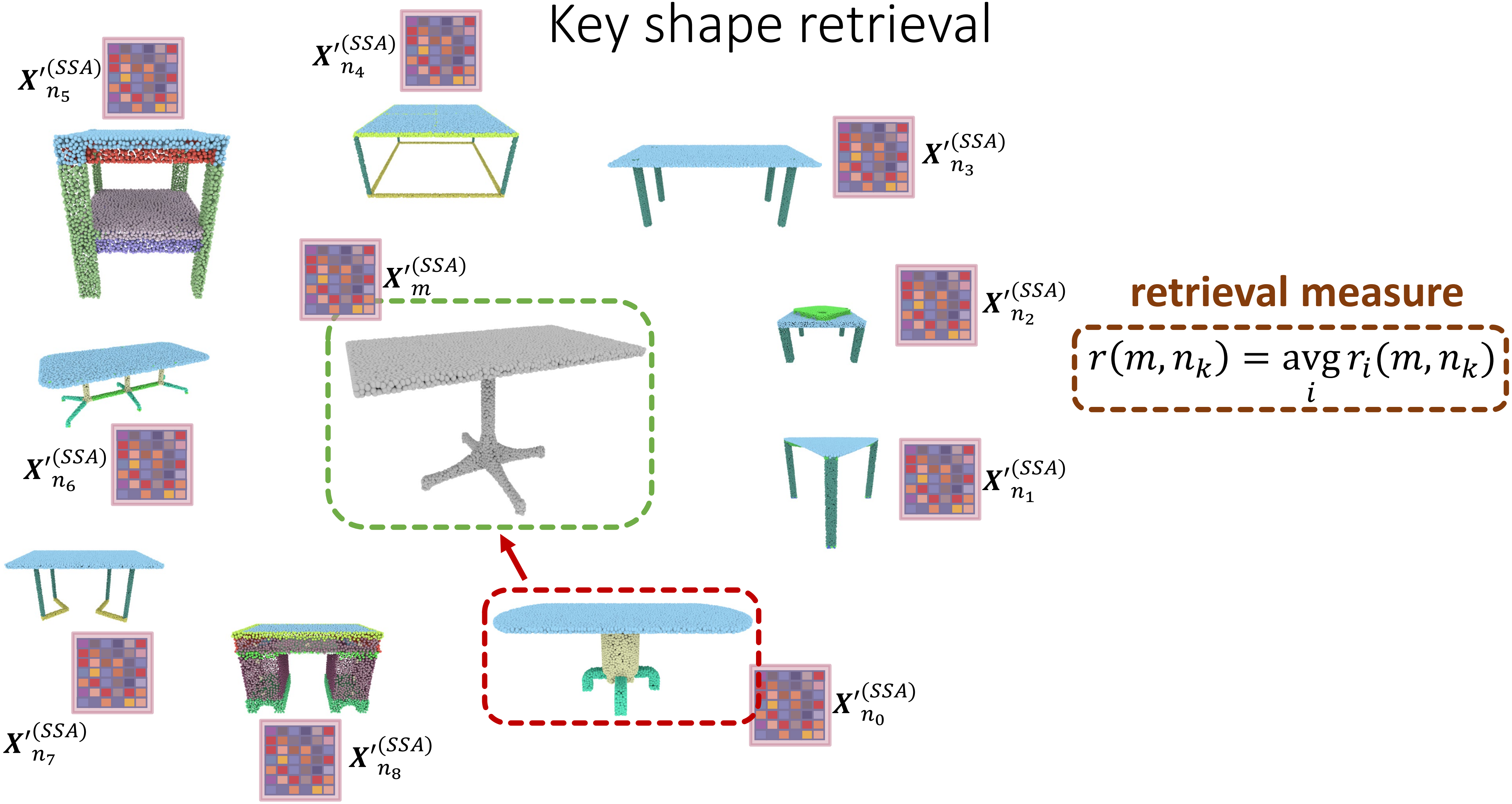


$$r_i(m, n_k) = \max_j \boldsymbol{S}_{m,n_k}[i,j]$$

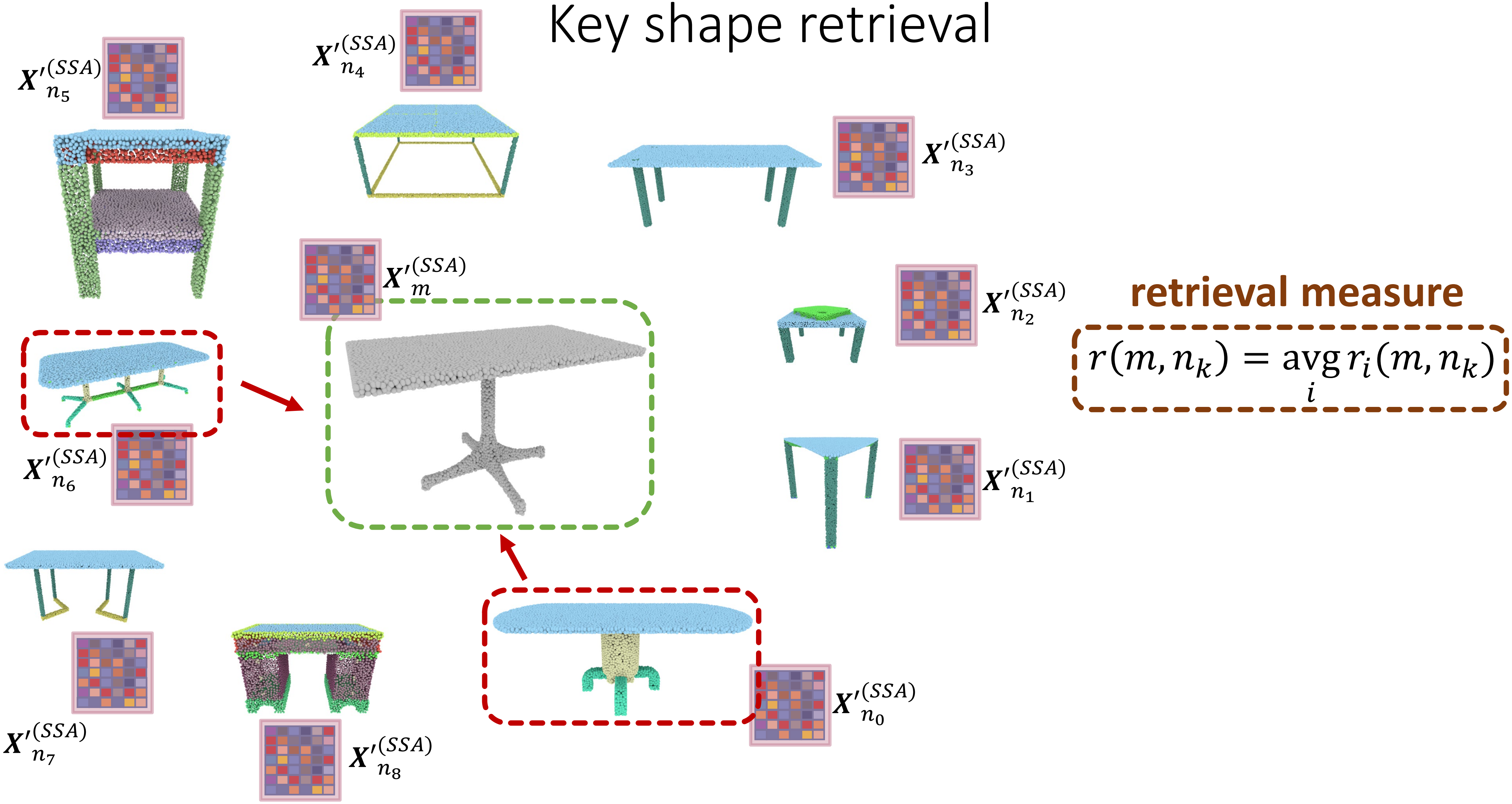
Key shape retrieval



Key shape retrieval

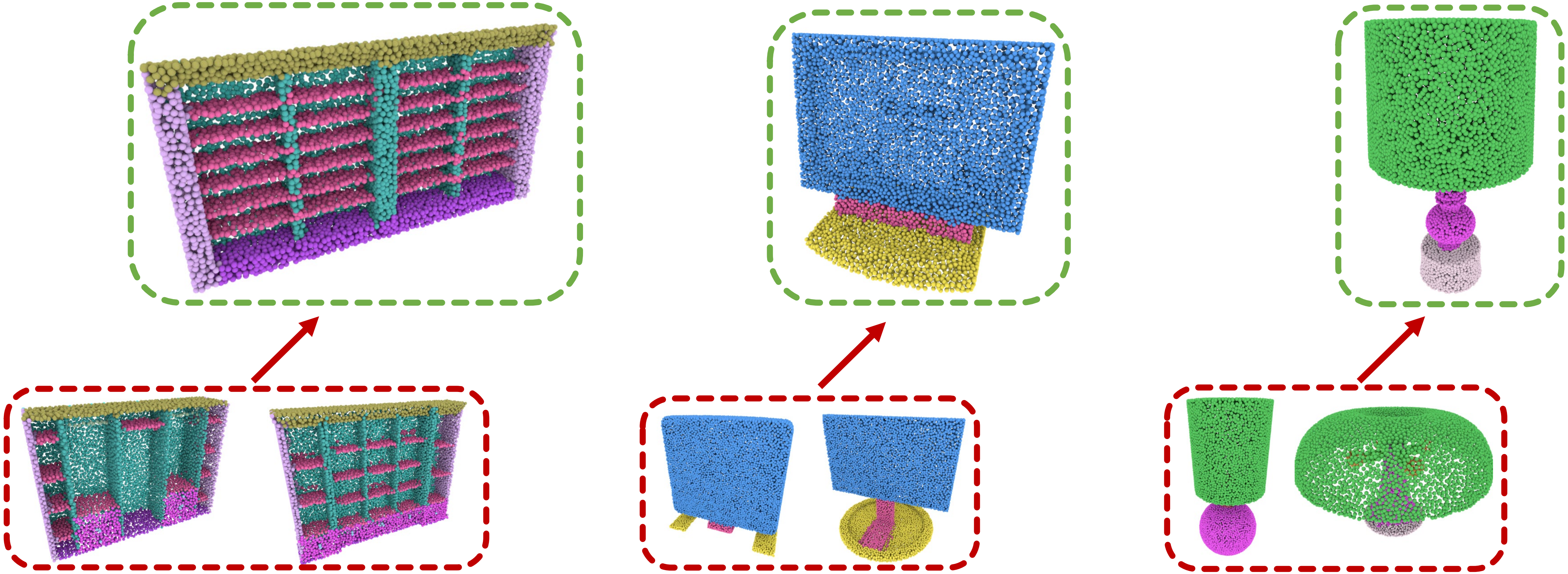


Key shape retrieval



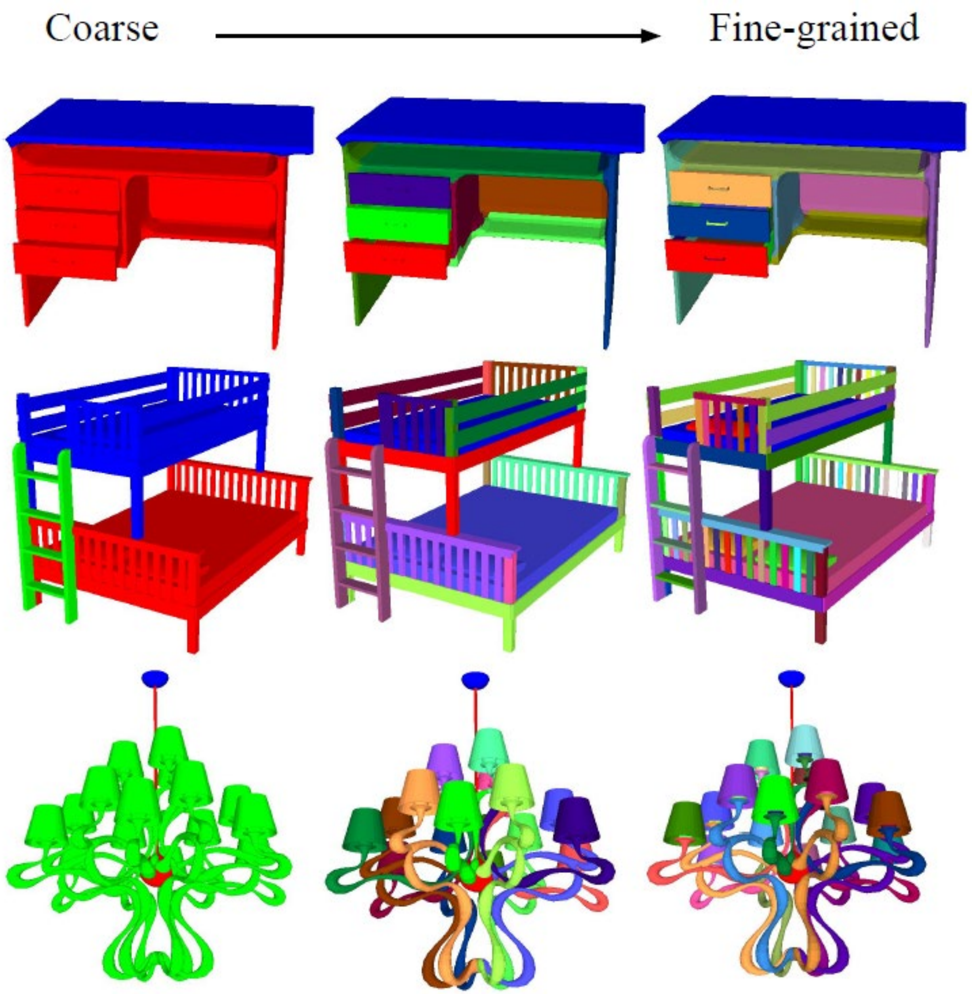
Key shape retrieval: Examples

query shapes



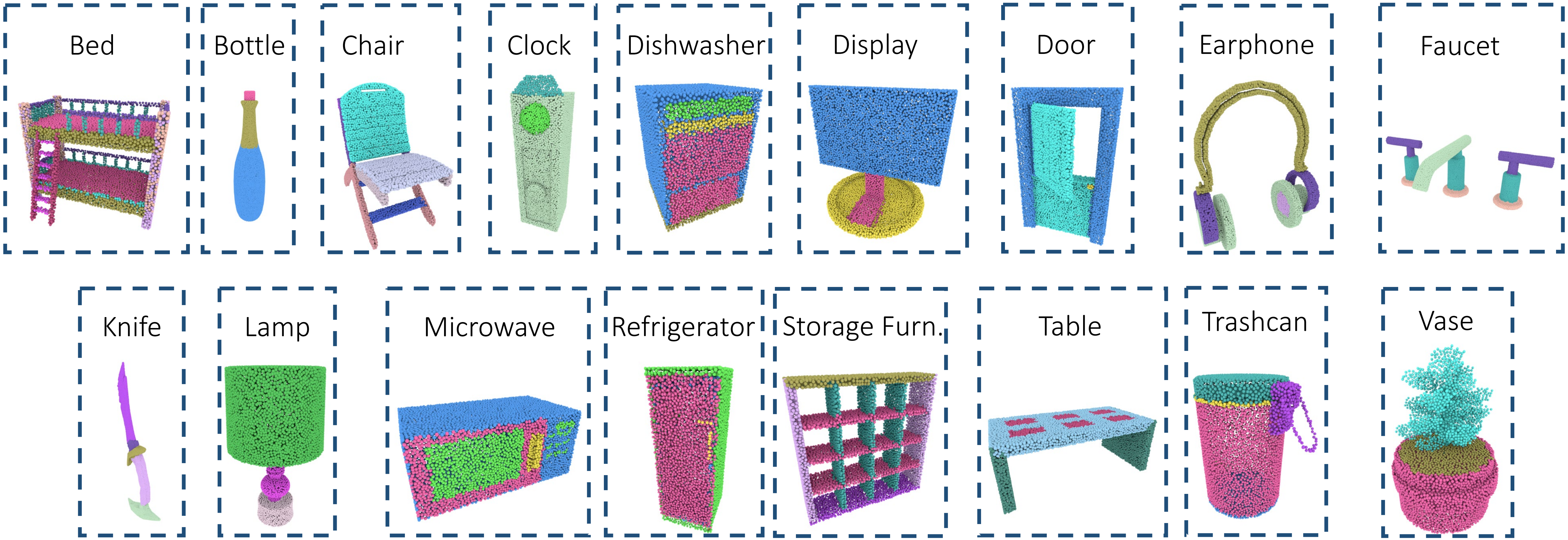
key shapes

PartNet dataset



[Mo et al. 2019]

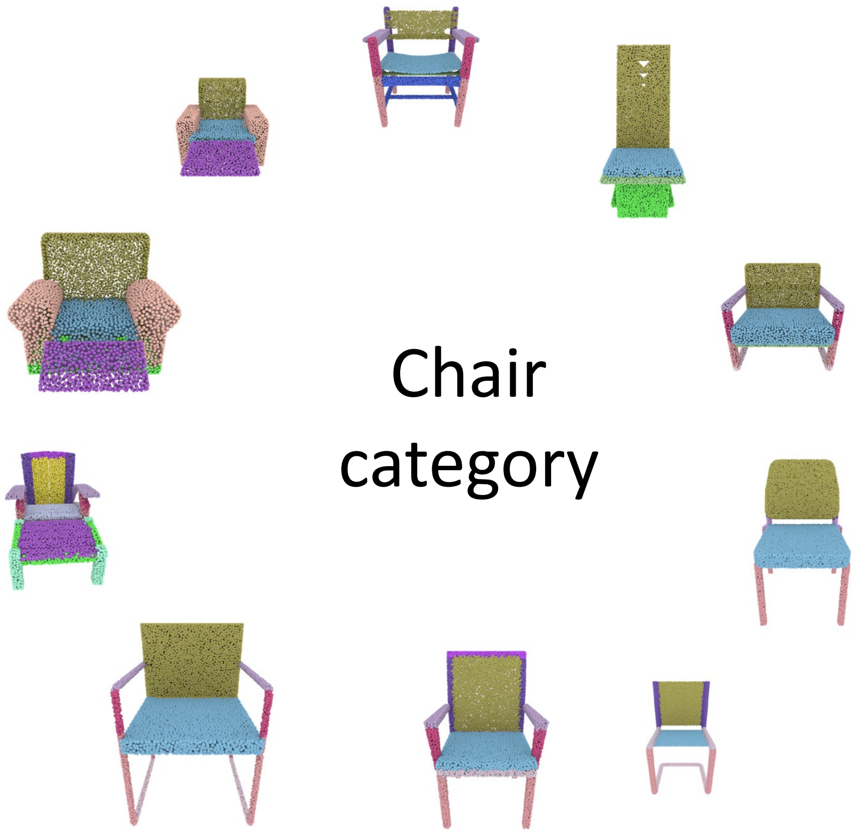
PartNet dataset



[Mo et al. 2019]

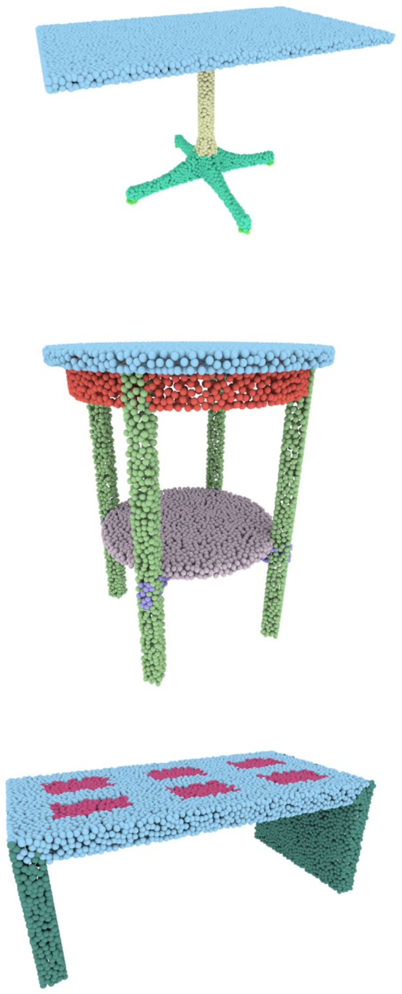
Examples of shape collections

5,707 training shapes



4,489 training shapes

Training details: Loss

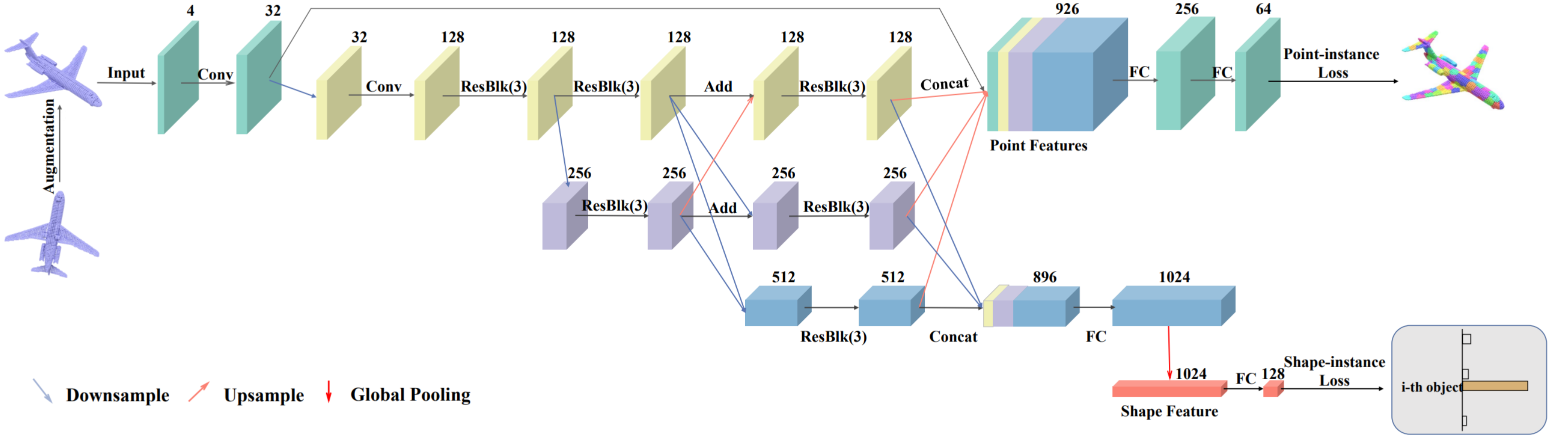


training
data

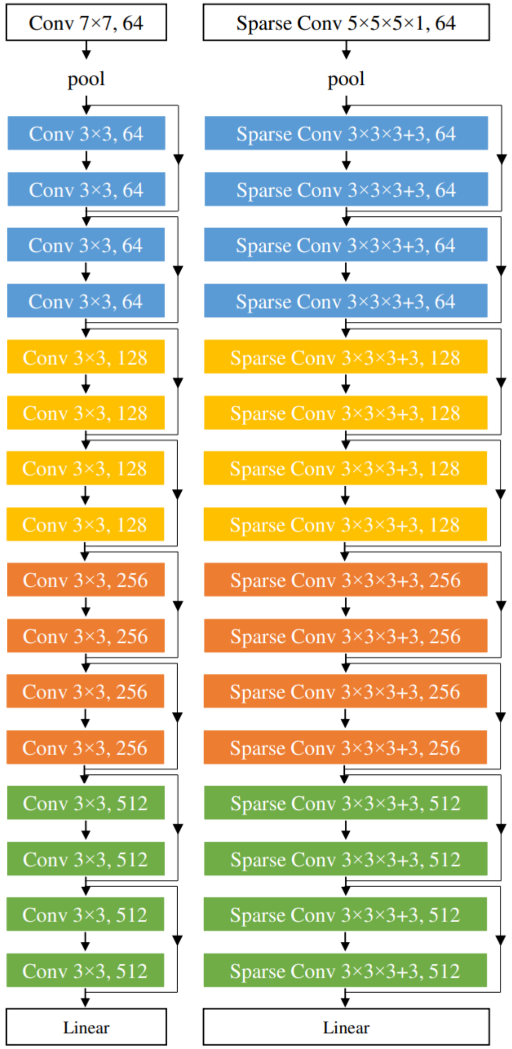
$$L_{CE} = -\sum_{\boldsymbol{p}_i \in \mathcal{S}_k} \widehat{\boldsymbol{q}}_i \log \boldsymbol{q}_i$$

$\mathcal{S}_k$: shape $k = \{\boldsymbol{p}_i\}_{i=1}^{P_k}$
$\widehat{\boldsymbol{q}}_i$: ground-truth one-hot label vector for point $\boldsymbol{p}_i$
$\boldsymbol{q}_i$: predicted label probabilities for point $\boldsymbol{p}_i$

Training details: Backbones

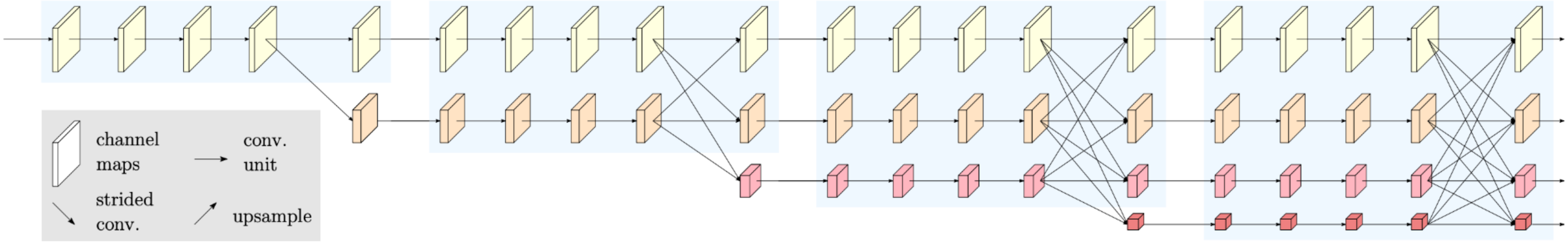


MID-FC [Wang et al. 2021]



MinkowskiNet [Choy et al. 2019]

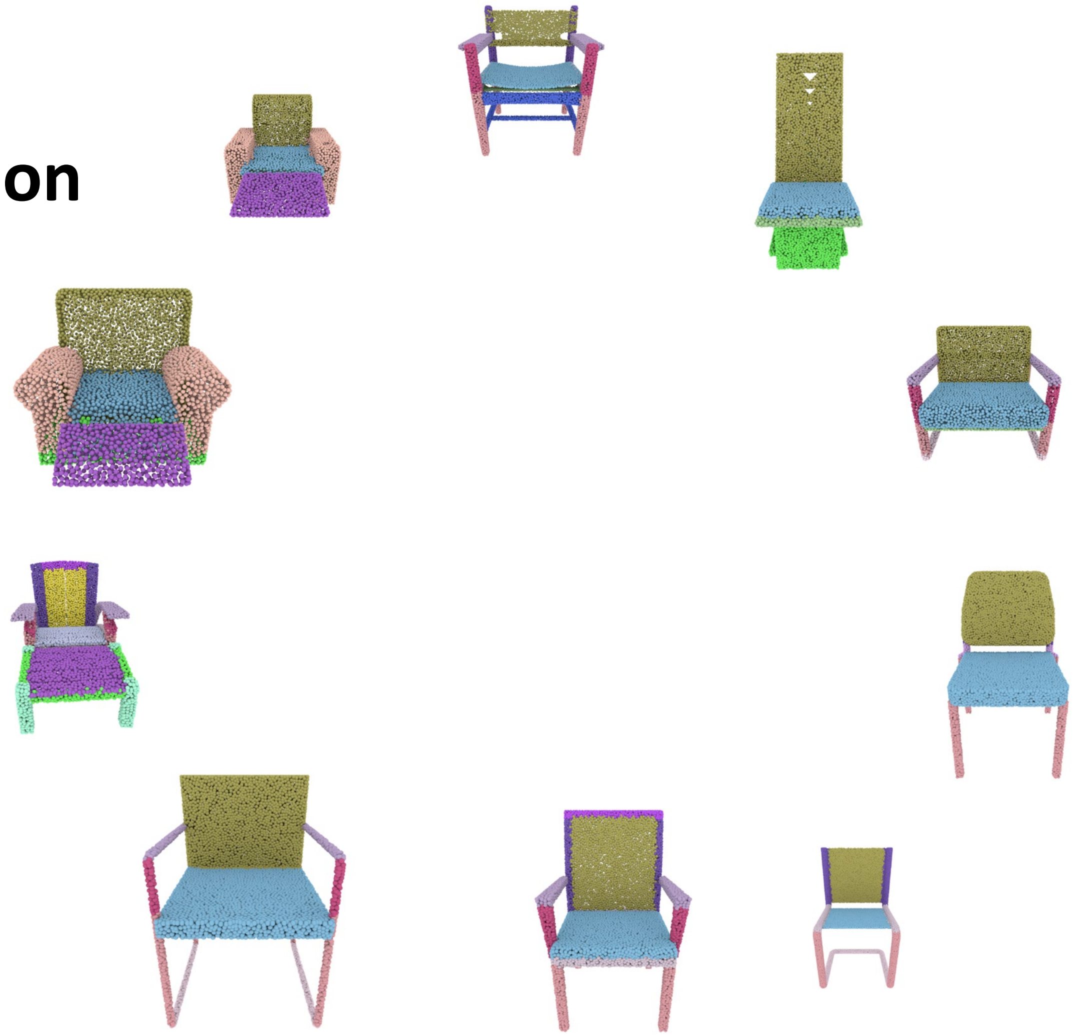
Training details: Backbones



HRNet [Wang et al. 2021]

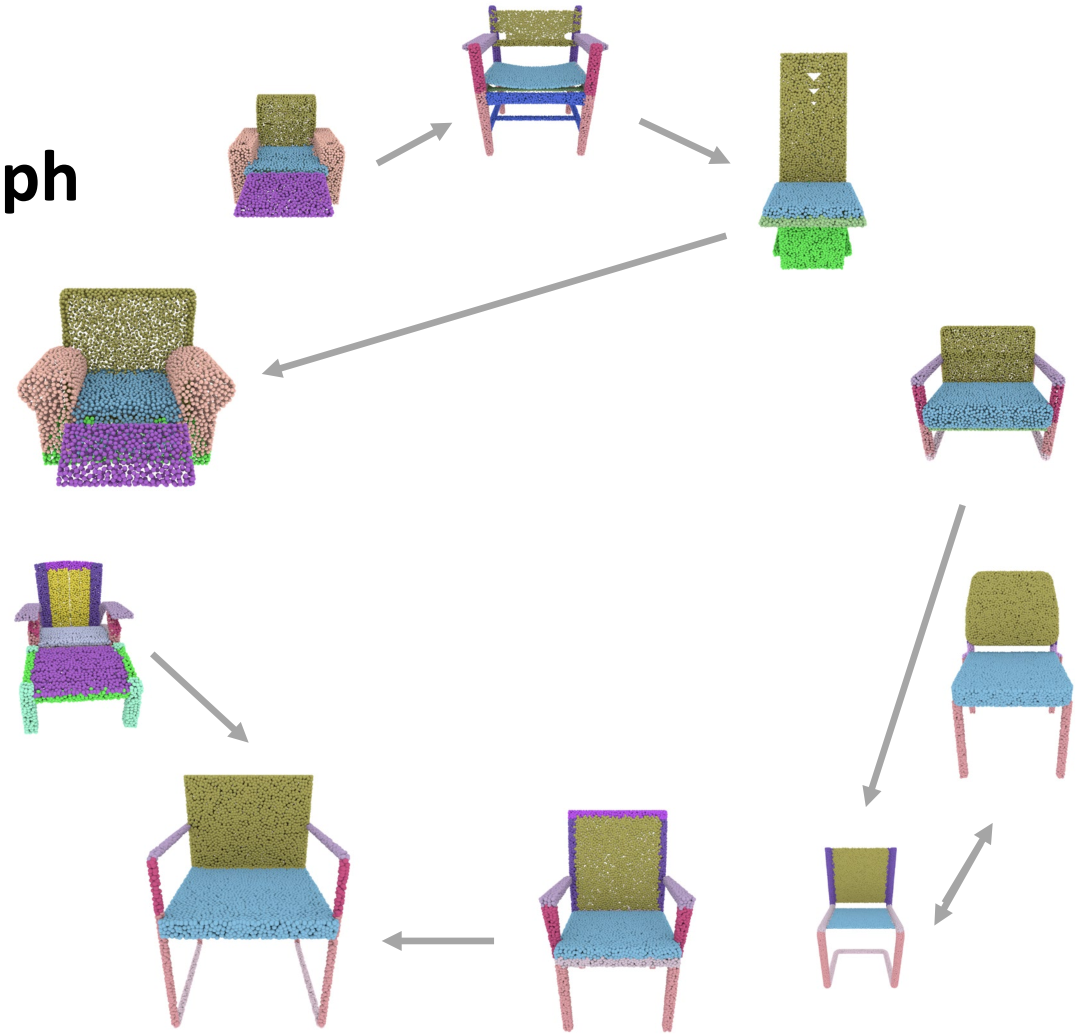
Training details: Collection graph

Shape Collection



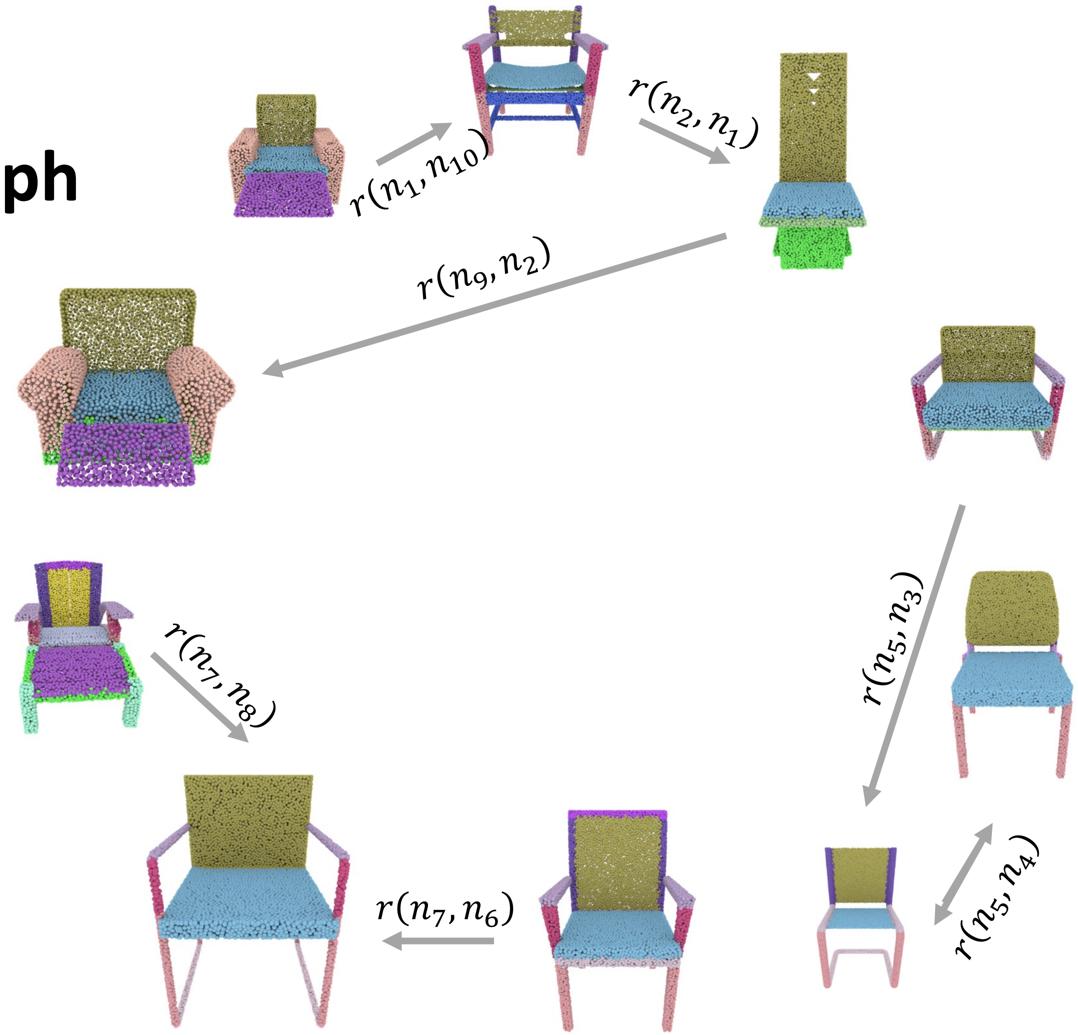
Training details: Collection graph

Collection graph



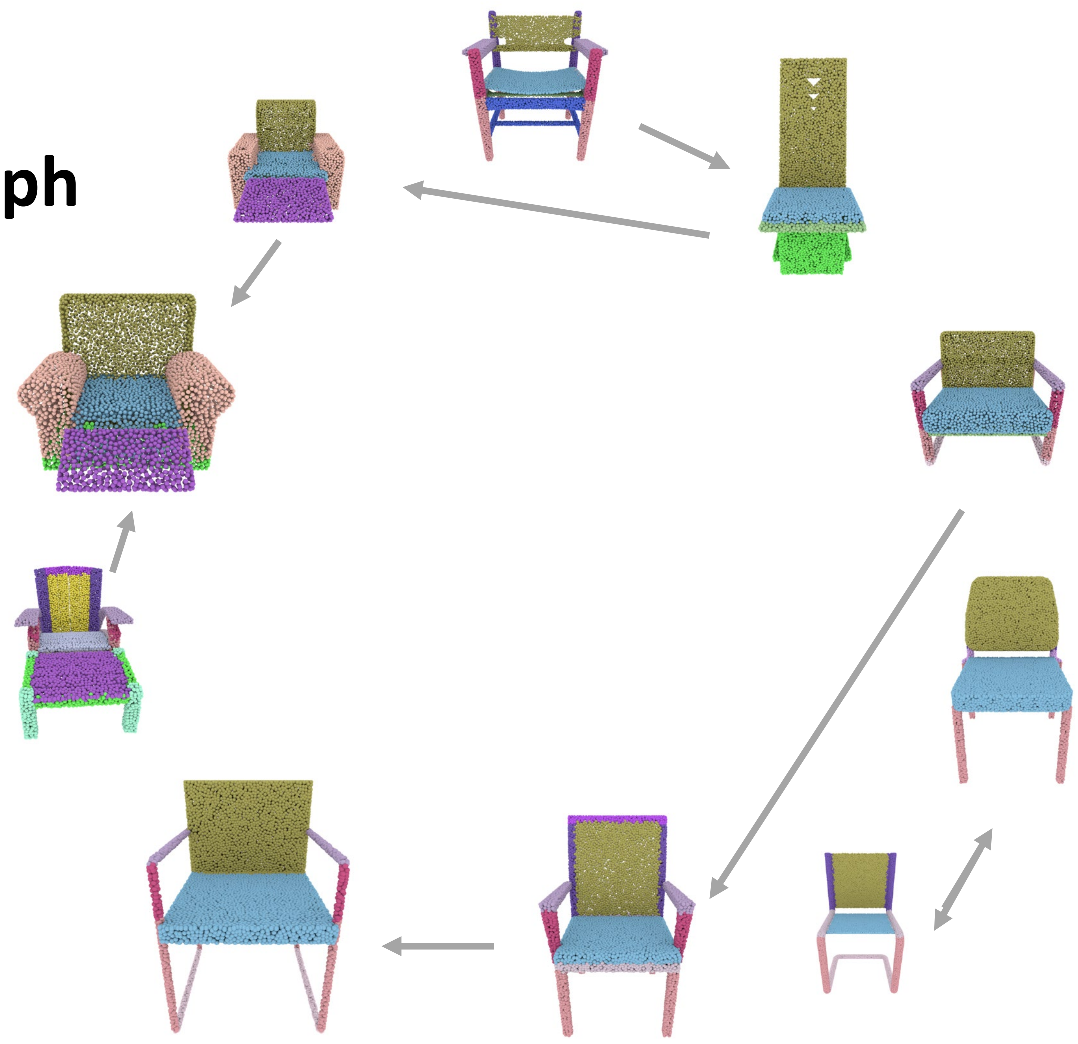
Training details: Collection graph

Collection graph



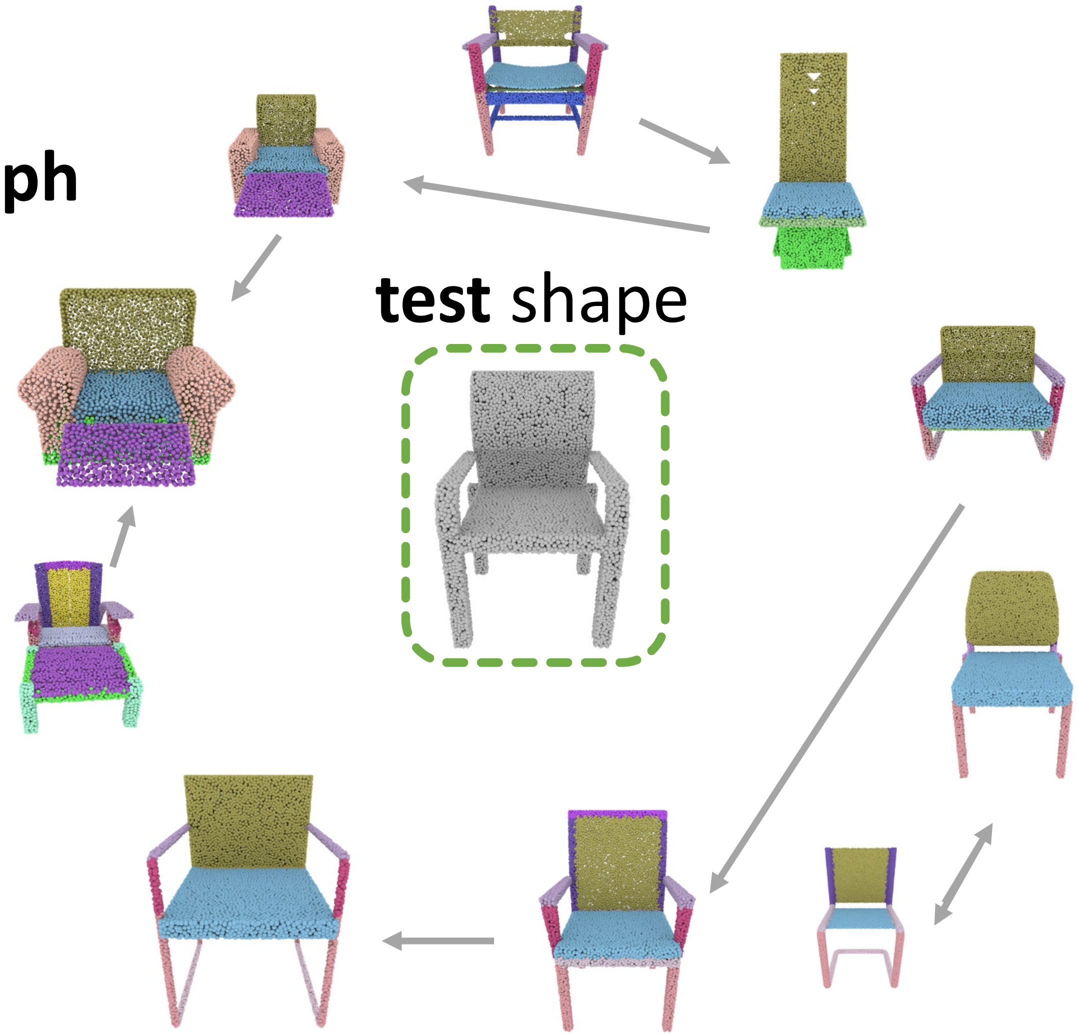
Training details: Collection graph

Collection graph

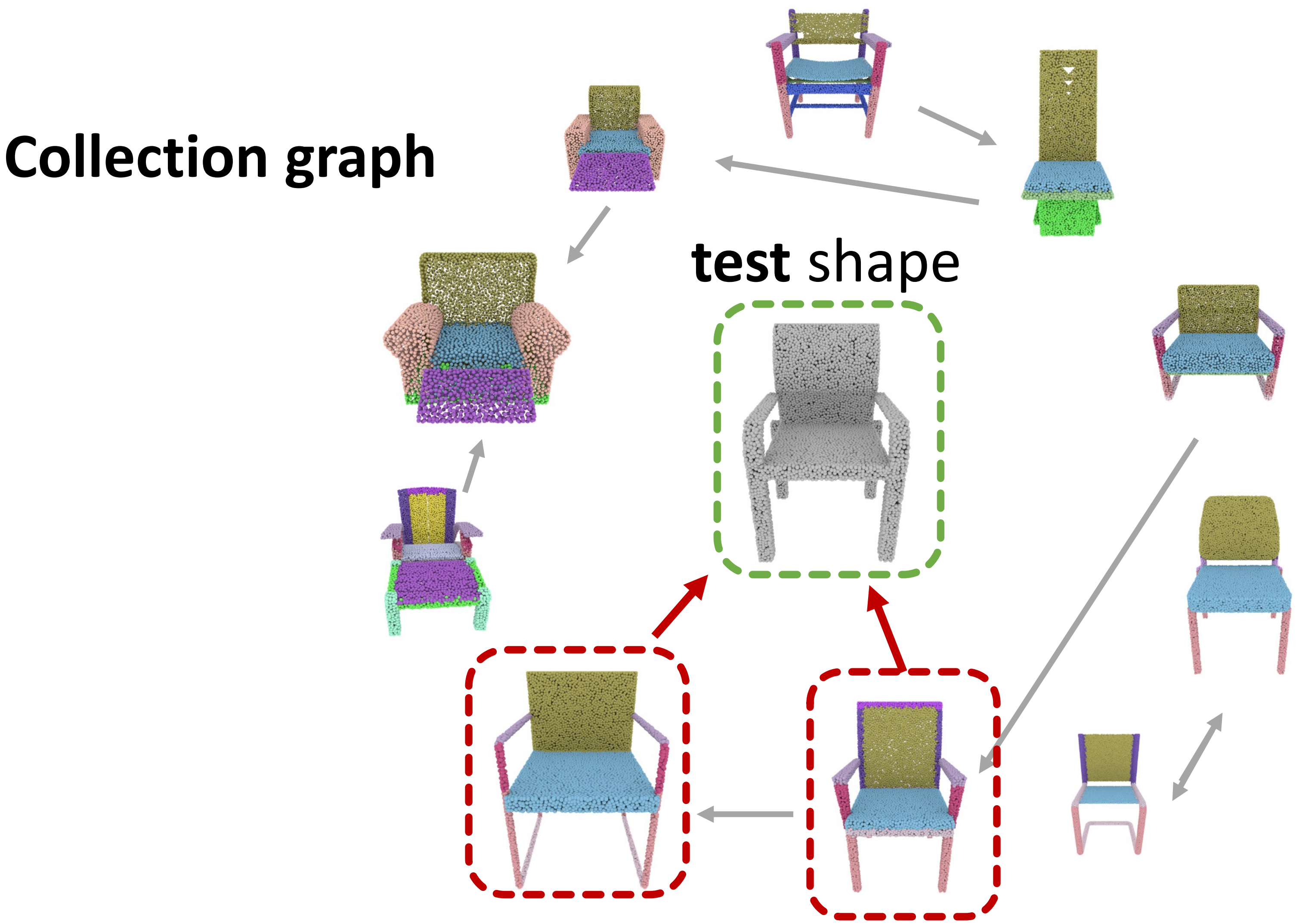


Inference: Collection graph

Collection graph



Inference: Collection graph



Results

Method	Part IoU

Results: MinkowskiNet variants

Method	Part IoU
MinkHRNet	48.0

Results: MinkowskiNet variants

Method	Part IoU
MinkHRNet	48.0
MinkHRNetCSN-SSA	48.7

+0.7%

Results: MinkowskiNet variants

Method	Part IoU
MinkHRNet	48.0
MinkHRNetCSN-SSA	48.7
MinkHRNetCSN-K1	**49.9**
MinkHRNetCSN-K2	49.7

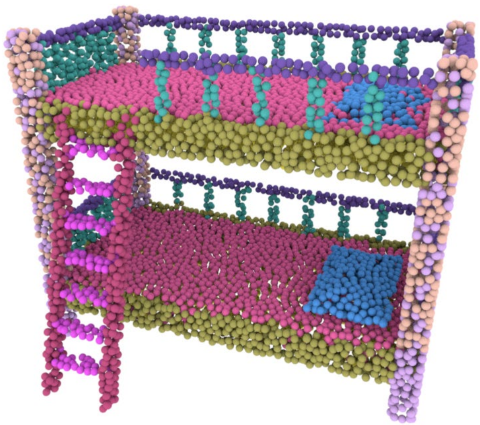
Results: MinkowskiNet variants

Method	Part IoU
MinkHRNet	48.0
MinkHRNetCSN-SSA	48.7
MinkHRNetCSN-K1	**49.9**
MinkHRNetCSN-K2	49.7

+1.2%

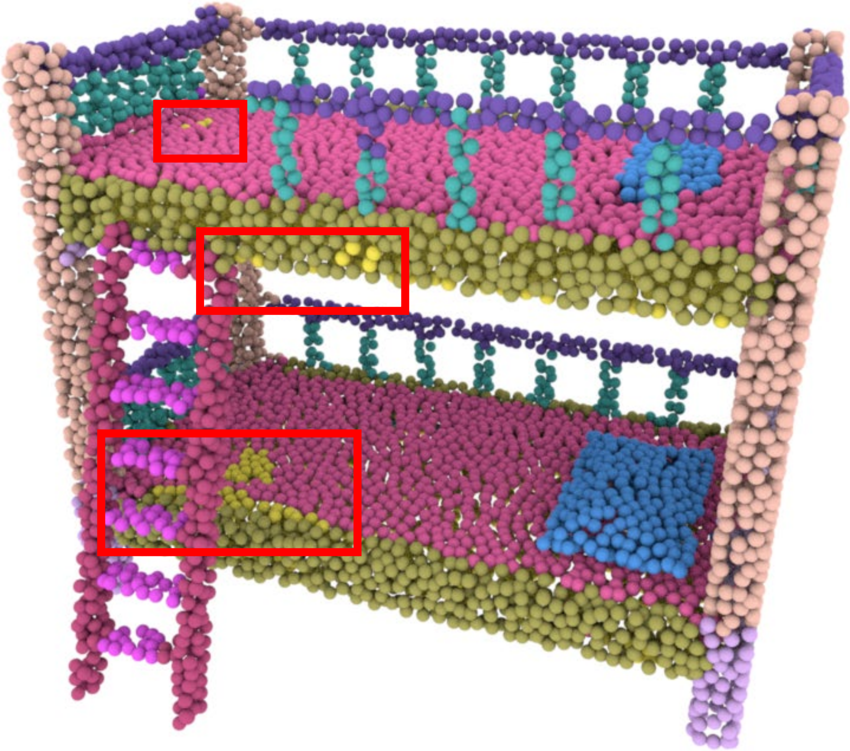
Results: MinkowskiNet variants

Ground truth



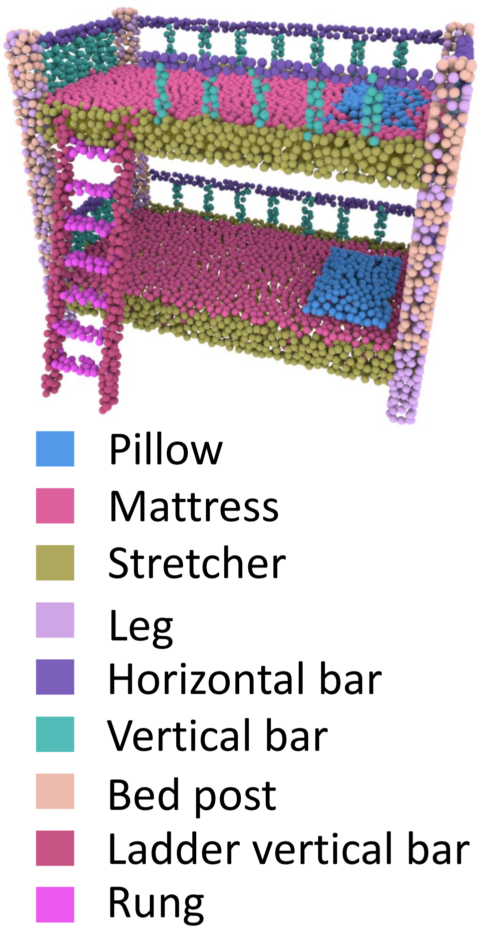
- Pillow
- Mattress
- Stretcher
- Leg
- Horizontal bar
- Vertical bar
- Bed post
- Ladder vertical bar
- Rung

MinkHRNet

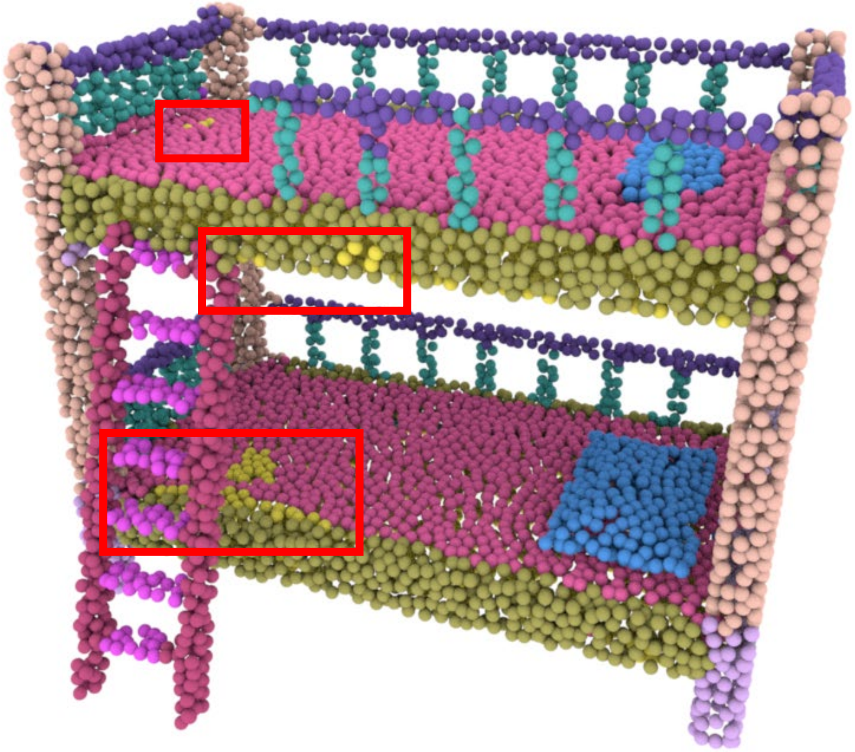


Results: MinkowskiNet variants

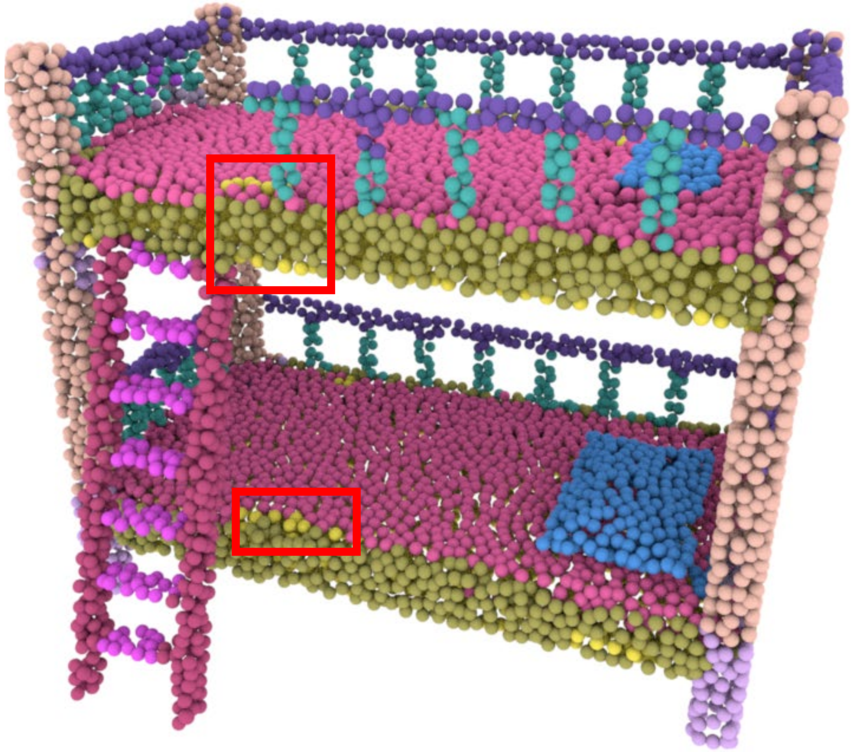
Ground truth



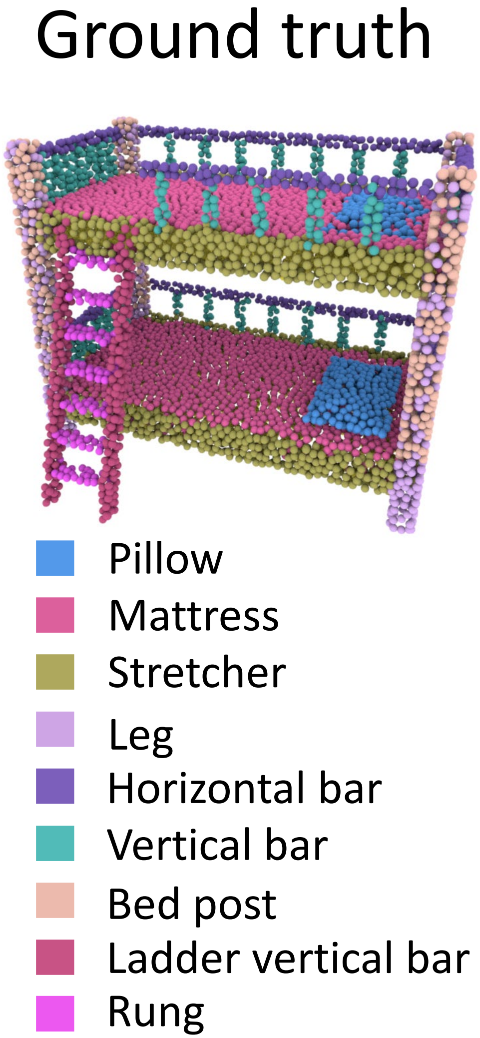
MinkHRNet

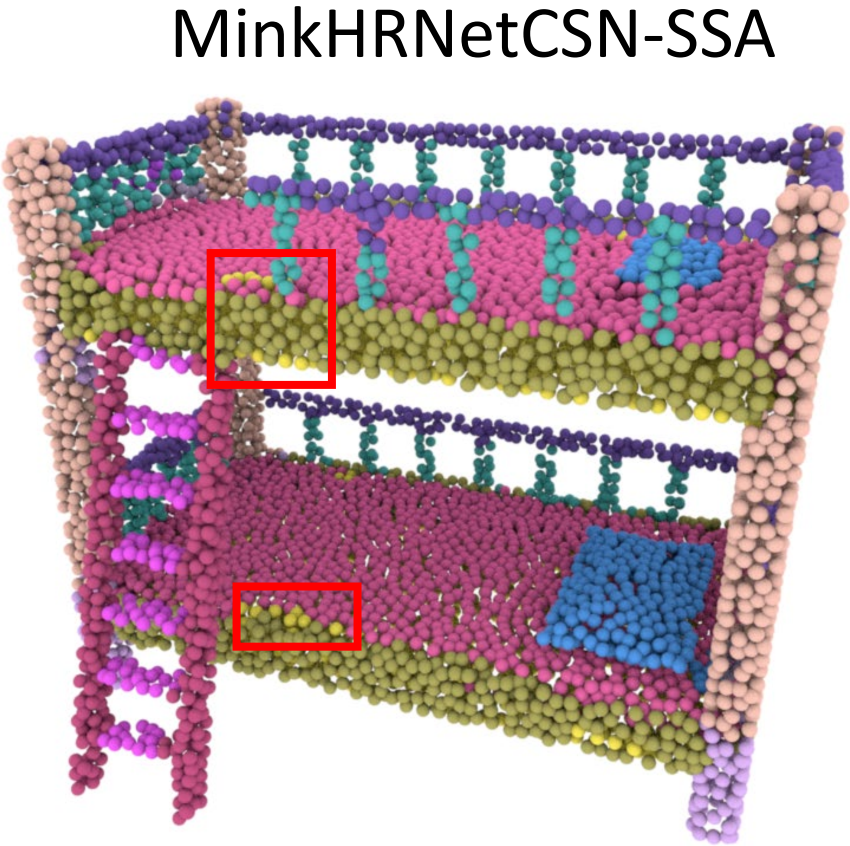


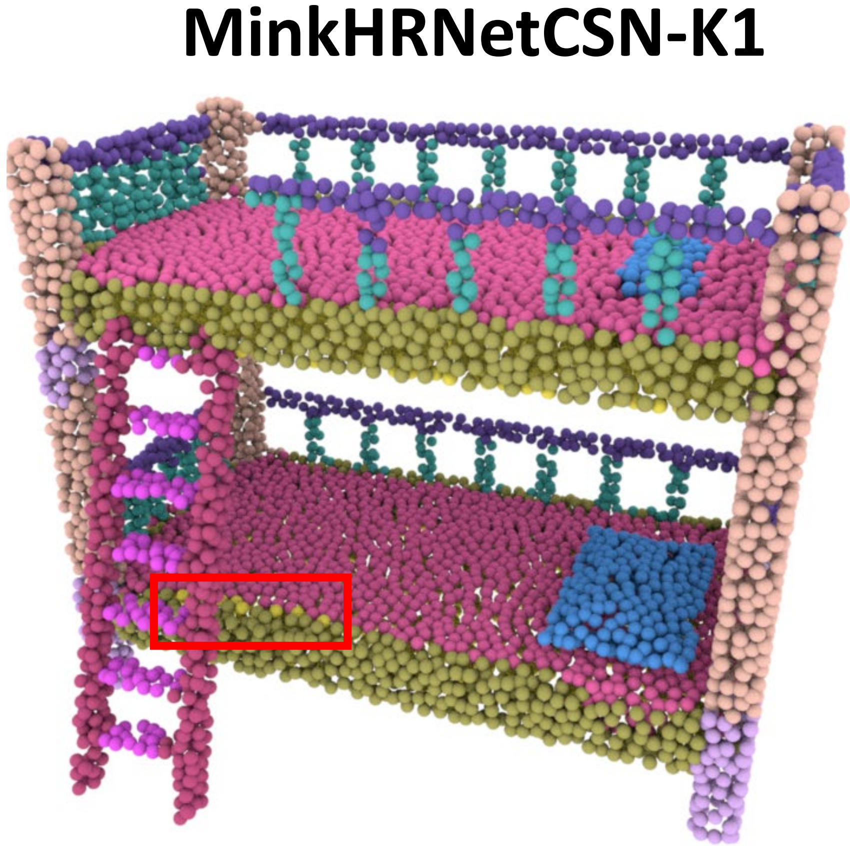
MinkHRNetCSN-SSA



Results: MinkowskiNet variants







Results: MID-FC variants

Method	Part IoU
MID-FC	60.8

Results: MID-FC variants

Method	Part IoU
MID-FC	60.8
MID-FC-CSN-SSA	61.8

+1.0%

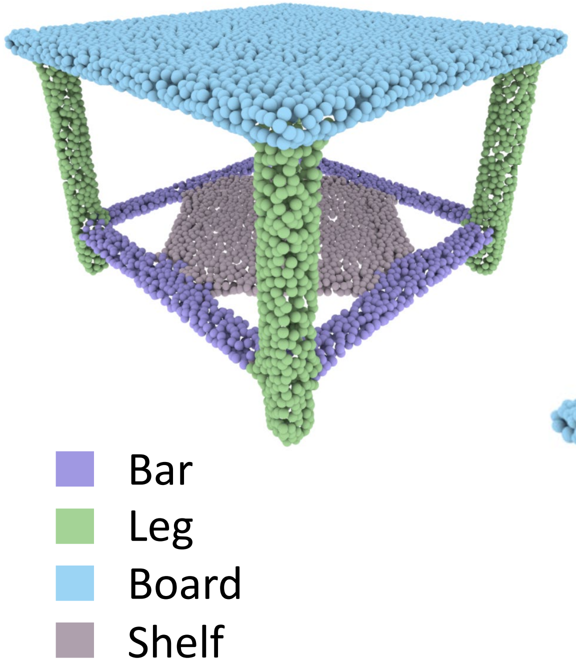
Results: MID-FC variants

Method	Part IoU
MID-FC	60.8
MID-FC-CSN-SSA	61.8
MID-FC-CSN-K1	61.9
MID-FC-CSN-K2	61.9
MID-FC-CSN-K3	62.0
MID-FC-CSN-K4	**62.1**
MID-FC-CSN-K5	62.0

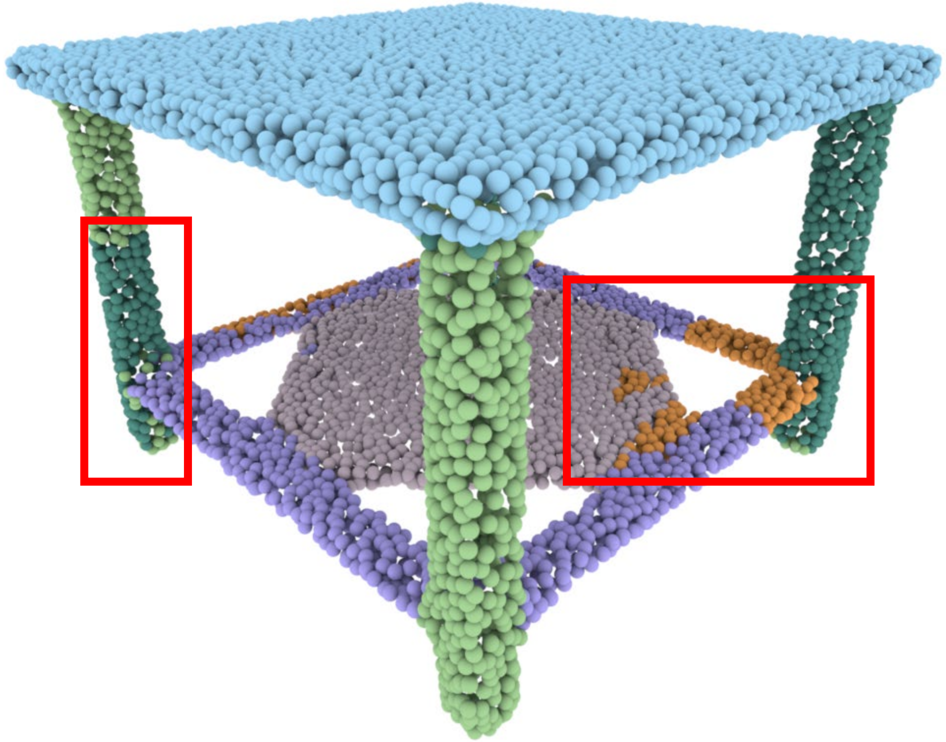
+0.3%

Results: MID-FC variants

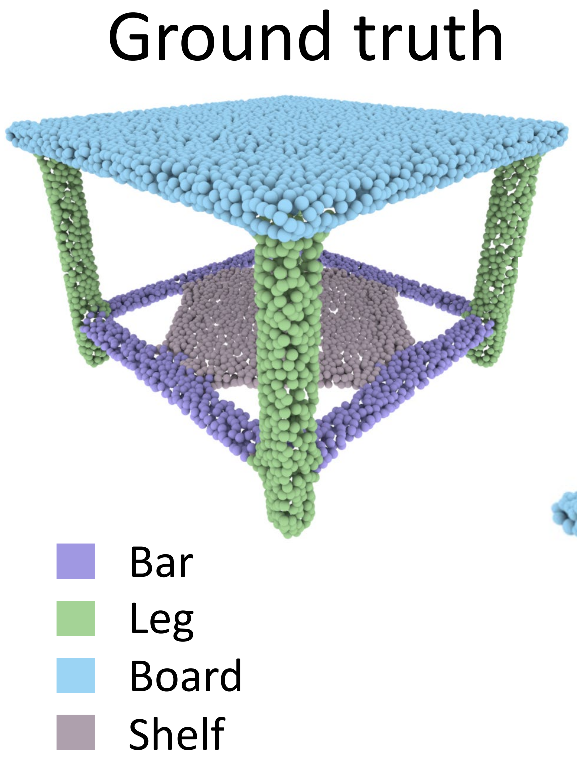
Ground truth

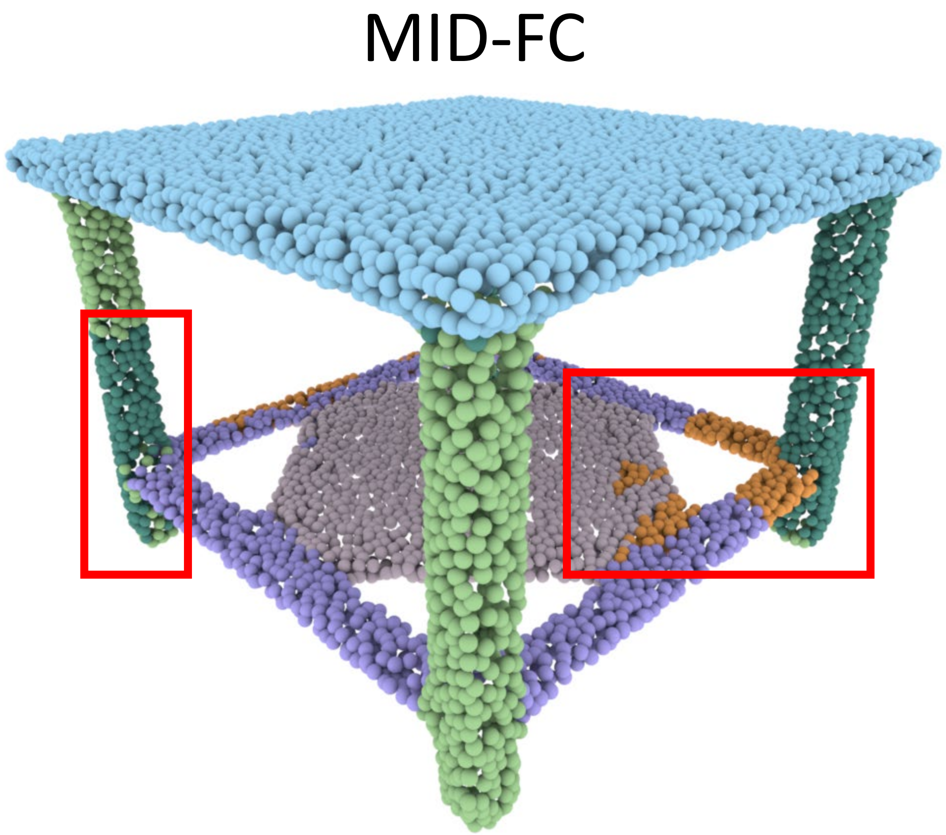


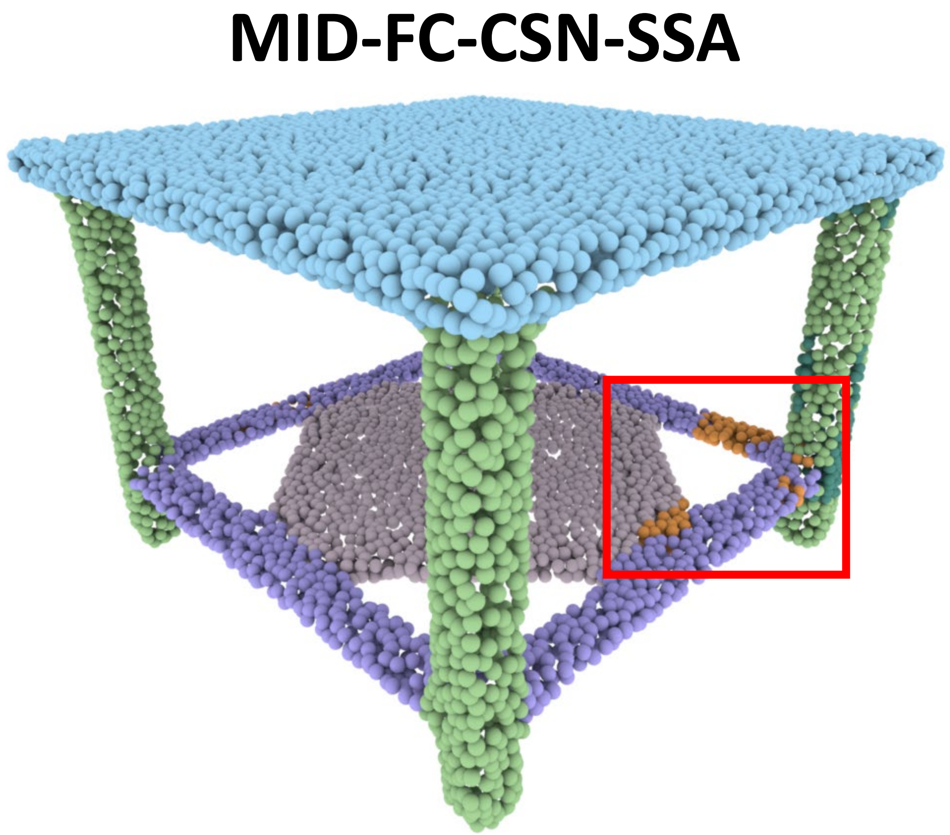
MID-FC



Results: MID-FC variants

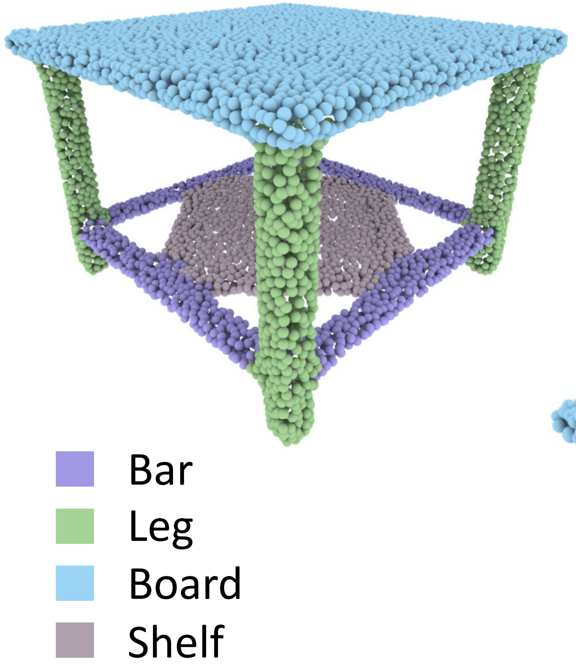




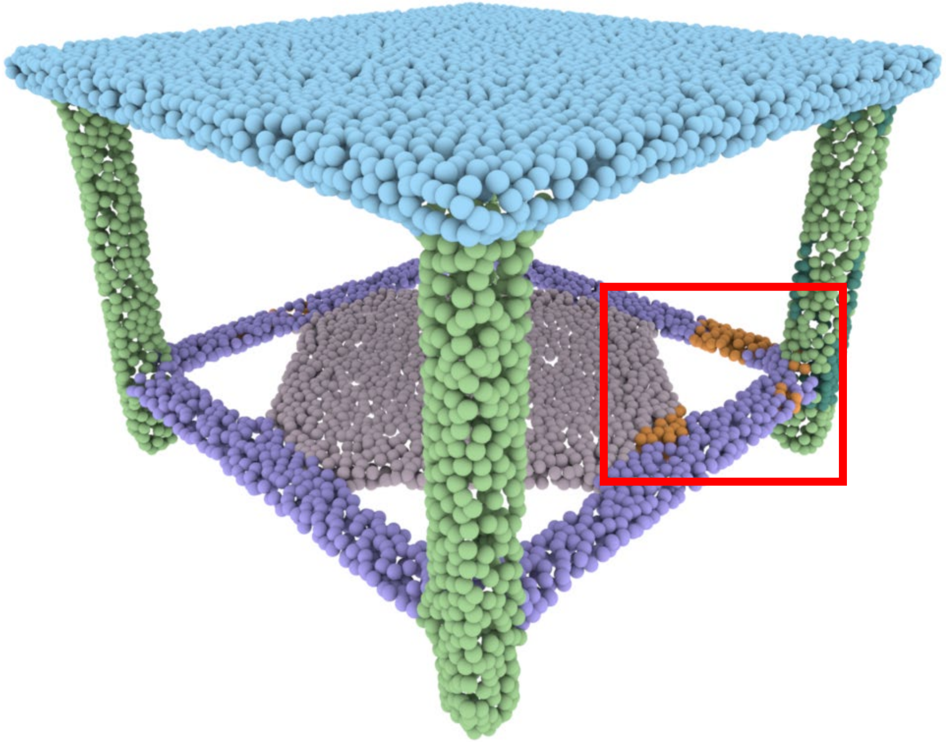


Results: MID-FC variants

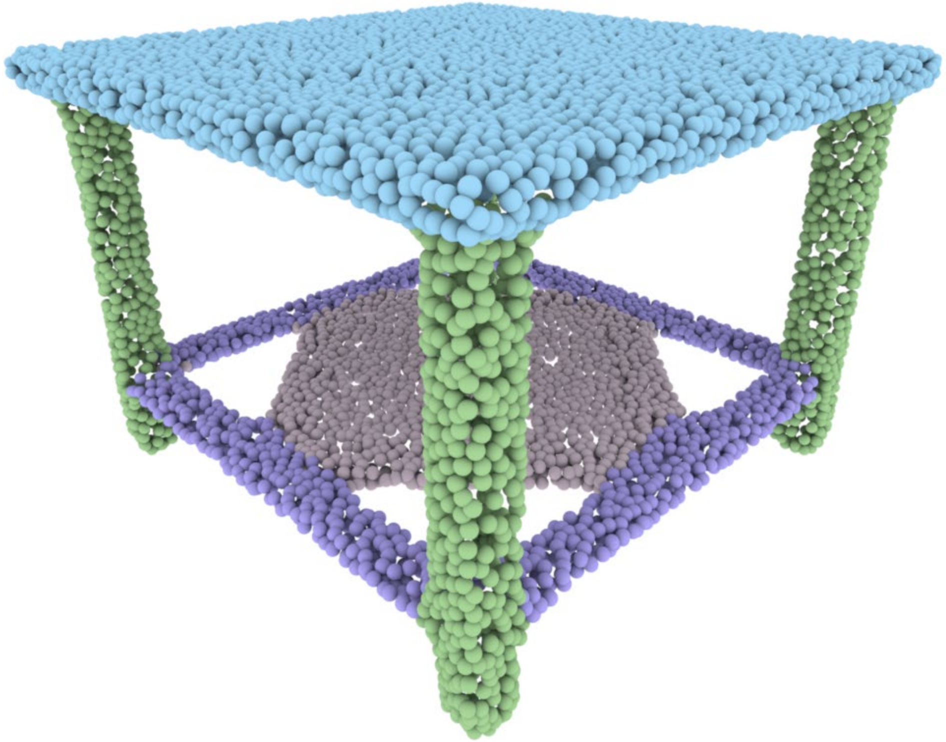
Ground truth



MID-FC-CSN-SSA



MID-FC-CSN-K4



Results: Comparison with other methods

Method	Part IoU
ResGCN-28 (Li et al. 2023)	45.1
CloserLook3D (Liu et al. 2020)	53.8
MinkResUNet (Choy et al. 2019)	46.8
MinkHRNetCSN-K1 (ours)	49.9
MID-FC (Wang et al. 2021)	60.8
MID-FC-CSN-K4 (ours)	**62.1**

Results: Comparison with other methods

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MinkHRNetCSN-K1 (ours)	49.9
MID-FC (Wang et al. 2021)	60.8
MID-FC-CSN-K4 (ours)	**62.1**

+3.1%

Results: Comparison with other methods

Method	Part IoU
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MID-FC (Wang et al. 2021)	60.8
MID-FC-CSN-K4 (ours)	**62.1**

+1.3%

Results: Comparison with other methods

Method	Part IoU
ResGCN-28 (Li et al. 2023)	45.1
CloserLook3D (Liu et al. 2020)	53.8
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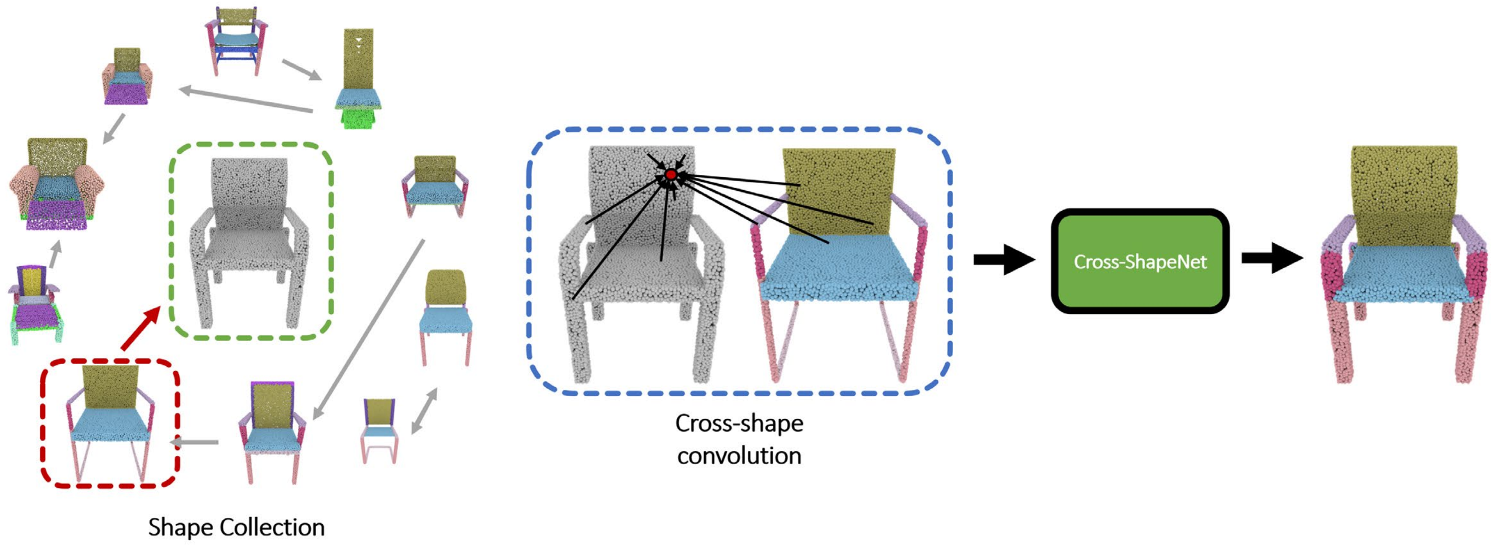
MinkHRNetCSN-K1 (ours)	49.9
MID-FC (Wang et al. 2021)	60.8
MID-FC-CSN-K4 (ours)	**62.1**

+1.3%

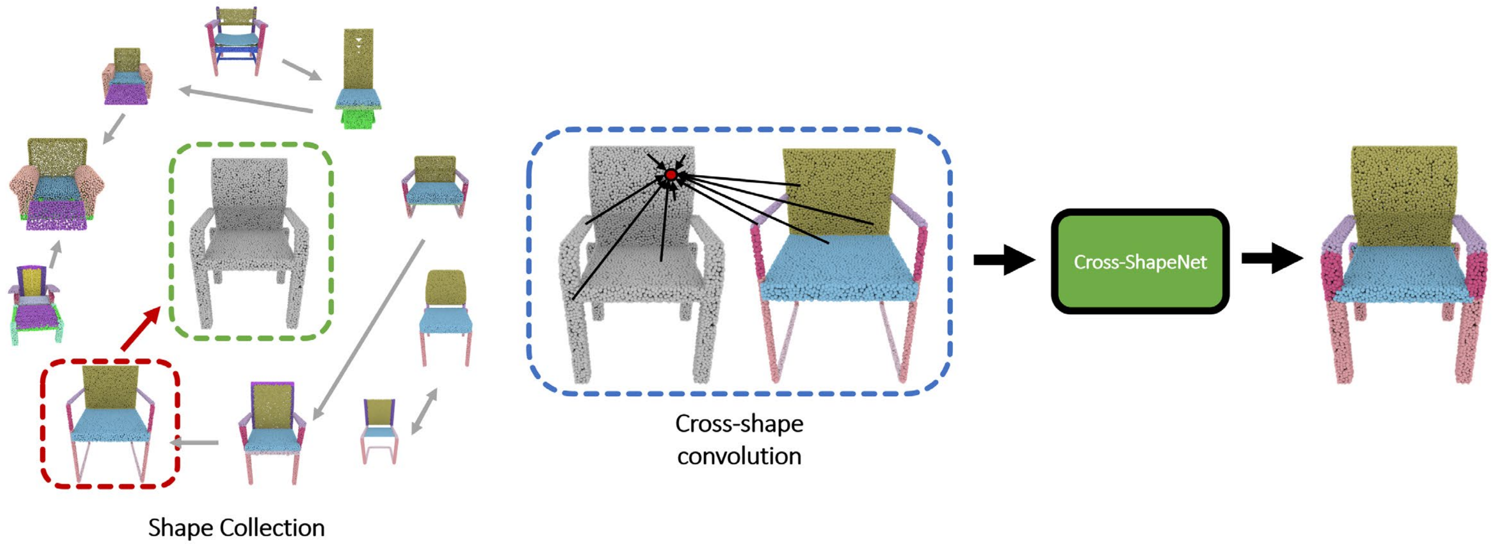
SOTA performance on the PartNet dataset

Summary



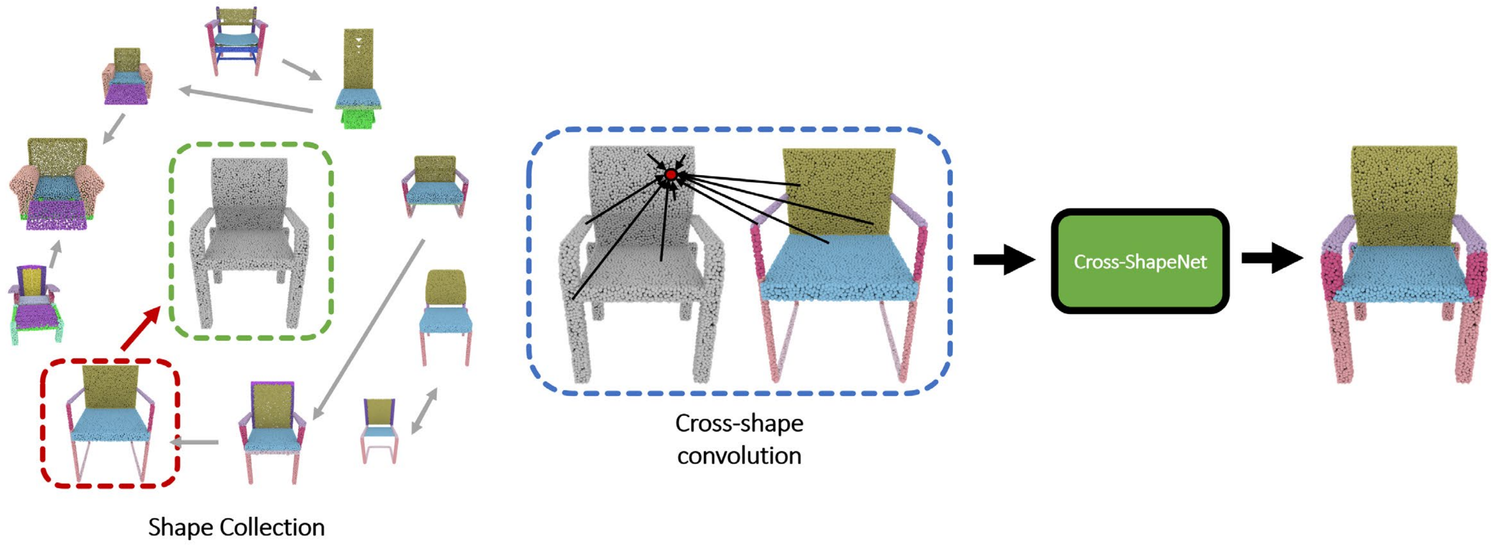
- Enable long range point feature interactions **across shapes**

Summary



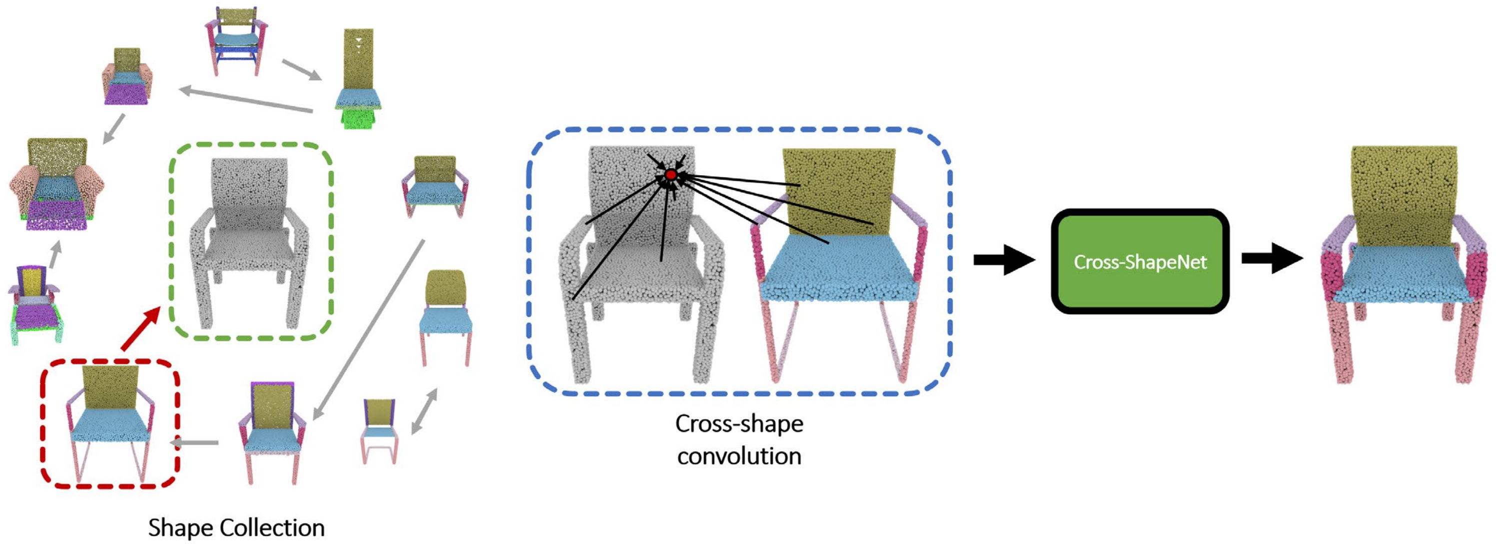
- Enable long range point feature interactions **across shapes**
- Introduce a **novel cross-shape attention** mechanism

Summary



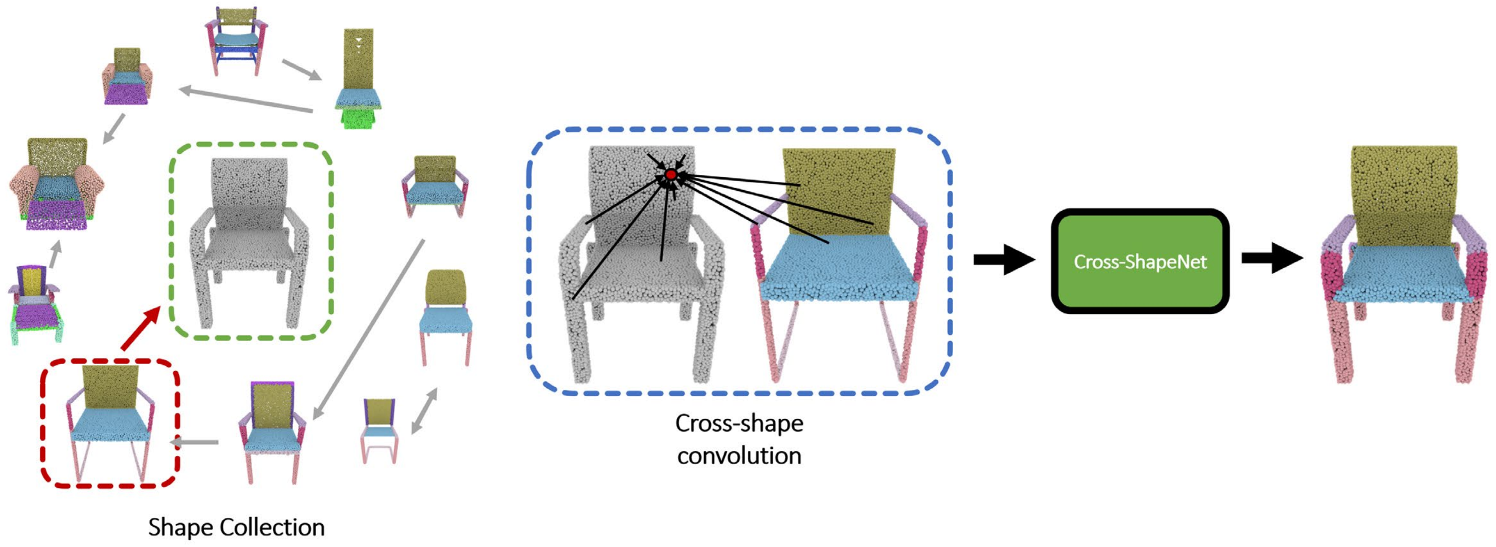
- Enable long range point feature interactions **across shapes**
- Introduce a **novel cross-shape attention** mechanism
- Retrieve **compatible shapes** for cross-shape attention

Summary



- Enable long range point feature interactions **across shapes**
- Introduce a **novel cross-shape attention** mechanism
- Retrieve **compatible shapes** for cross-shape attention
- **SOTA performance** on PartNet

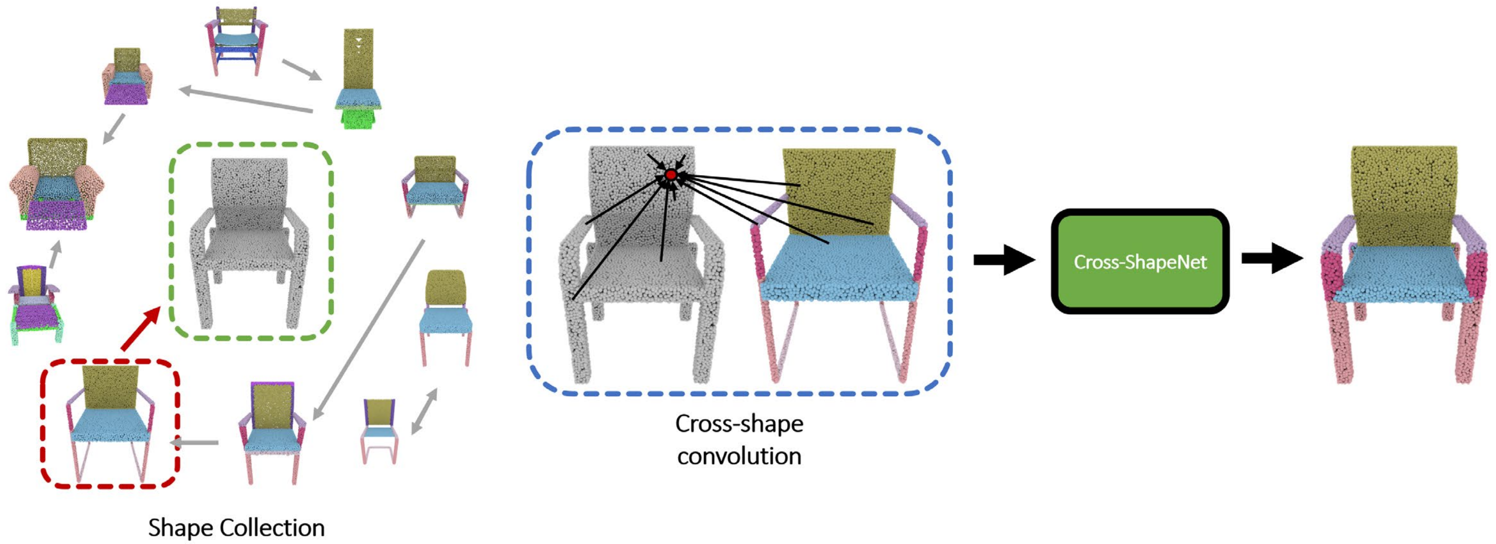
Summary



Limitations:

- **Increased computational cost** due to shape retrieval

Summary



Limitations:

- **Increased computational cost** due to shape retrieval
- Currently no support for **multi-object scenes**

Thank you!

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https://marios2019.github.io/CSN/